Essays on Financial Contagion and Financial Crises

Dinesh Prasad Gajurel

(MPhil, MA, MBS, LLB, BBS)

Tasmanian School of Business and Economics

University of Tasmania

UNIVERSITY OF TASMANIA

This dissertation is submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

October 2015

Declaration of Originality

This dissertation contains no material which has been accepted for a degree or diploma by the University or any other institution, except by way of background information and duly acknowledged in the dissertation, and to the best of my knowledge and belief no material previously published or written by another person except where due acknowledgement is made in the text of the dissertation, nor does the dissertation contain any material that infringes copyright.

Dinesh Gajurel

Hobart, Tasmania

October 20, 2015

Preface

The essays in this dissertation represent collaborative efforts with my superviosrs. Chapter 2 is co-authored with Professor Mardi Dungey and published in the journal *Economic Systems*, Chapter 3 is joint work with Professor Mardi Dungey, Chapter 4 is co-authored with Professor Mardi Dungey and published in the *Journal of Banking and Finance* and Chapter 5 is a joint work with Professor Mardi Dungey, Dr. Nagaratnam Jeyasreedharan and Dr. Wenying Yao.

The publisher of the papers comprising Chapters 2 and Chapter 4 holds the copyright for that contents, and access to the materials should be sought from the respective journals. The remaining non-published content of the dissertation may be made available for loan and limited copying and communication in accordance with the Copyright Act 1968.

Acknowledgements

This dissertation could not have been possible without the advice and encouragement of my supervisors at the University of Tasmania.

First and foremost I would like to thank my supervisor, Professor Mardi Dungey, for her endless support, encouragement and guidance. She has always made herself available for help and advice and there has never been an occasion when I have knocked on her door and she hasn't given me time. The joy and enthusiasm she has for her research was contagious and motivational for me, even during tough times in the PhD pursuit. She has shown me, by way of example, what an outstanding academic (and person) should be. It has been a pleasure to work with her and I hope we continue collaborating on future research.

I gratefully acknowledge other members of my PhD supervisory committee for constructive advices and support. I am thankful to Dr. Nagaratnam Jeyasreedharan who pushed me to delve deeper in studying the question at hand. He deserves special mention for his mentorship during my final year of PhD. Without his support and confidence, I would have not completed my dissertation. I would like to thank Dr. Vitali Alexeev. His invaluable advice in quantitative aspects of my research has shaped my work and thoughts and will continue to influence my future research. I am also grateful to Dr. Wenying Yao for accepting to work jointly in Chapter 5. She has been a wonderful mentor and co-author. I would also like to thank Professor Graeme Wells for generously dedicating time to reading my drafts and for providing the excellent comments.

In addition, my research has benefited from comments and suggestions by many academics, including Professor Graciela Kaminsky, Professor Henk Berkman and the reviewers. I would like to thank participants at the Symposium on Performance of Finance Market at Deakin University, at the 42nd Australian Conference of Economists at Murdoch University, at seminars at the Economic Society of Australia Tasmania Branch and at the University of Tasmania for helpful comments. I would like to thank my colleagues Biplob, Fabio, Graham, Sayeed, Sophie and Steve for their comments and suggestions.

Most importantly, my PhD journey would have not been possible without the love and support of my family. Words cannot express how grateful I am to my mother and father for all the sacrifices they have made on my behalf. Without them, I most certainly would not be where I am today. Special and profound thanks to my beautiful wife, Sabina for her unconditional and complete love, care and support, and taking complete care of Samarpan, our little boy. She is an amazing mother. I am always indebted to my parents-in-law for their love, courage and support. I should not forget to mention my brother, Radhe Shyam for his contribution in my academic advancements. I am thankful to my cousin brother, Deepak and his wife, Sabita for making lively family environment here in Hobart.

Finally, I am greateful to the University of Tasmania for the scholarship and to Professor Mardi Dungey for conference travel funding.

Dinesh Gajurel

Hobart, Tasmania

October 2015

Abstract

Financial crises spread across countries through a variety of channels. A crisis originating in one market may propagate in an alternative form and have different impact in another market. The spread of crises through existing trade and financial linkages may be anticipated; however, during periods of stress, transmission in excess of these linkages is frequently observed. It is this excess transmission, known as financial contagion, which is the focus of this dissertation.

Contagion is one of the important mechanisms by which a financial crisis may become systemic. Consequently it is important for policy makers and market participants alike to identify the channels by which crises transmit and to assess the extent of contagion risk in global markets. Understanding contagion risk helps frame policies to reduce the immediate impact of a crisis and to undertake long-term structural reform policies for financial stability.

This dissertation examines contagion between international equity markets during the global financial crisis (GFC) of 2007-2009. It identifies channels (common factor, idiosyncratic factor, structural shift and volatility spillovers) by which crisis shocks transmit across borders and uses a variety of econometric techniques to test for the existence and extent of contagion during this period. The channels of contagion identified are shown to relate to the probability and severity of banking crises. While existing research largely focuses on tests for contagion at aggregate market level, this thesis compares aggregate results with those for the financial sector, and finds – perhaps surprisingly – that there is somewhat less evidence at the financial sector level.

The empirical evidence in the dissertation shows that both advanced and emerging equity markets are exposed to contagion risk through the idiosyncratic shocks emanating from the crisis originating market (here the US). While emerging markets are as affected as developed markets at aggregate market level, the financial sectors of advanced economies are less exposed to the idiosyncratic shock channel than the emerging markets. Banking sectors across the world are shown to be significantly exposed to contagion. Most have evidence of contagion from some or all four channels. However, contagion associated with the idiosyncratic shock channel has the largest impact – it increases the probability of a banking crisis by 27 percent, suggesting policy makers may wish to design policies aimed at mitigating these effects.

Finally, the dissertation empirically relates the evidence for systematic risk for large US financial firms with existing empirical measures of systemic risk. Using high frequency equity data to separate the responsiveness of these firms to jumps and continuous movements in market prices reveals that firms have higher jump beta than continuous beta. Further, the aggressiveness of the jump beta response of the institutions is positively related to systemic risk measured by capital shortfall and negatively to systemic risk measured by interconnectedness.

The evidence compiled in this thesis confirms the existence and extent of contagion effects across international equity markets, including their banking sectors, focusing on the crisis of 2007-2009. It offers empirical evidence on the relative importance of considering the source and channel of the crisis transmissions as well as the structure of the domestic banking sector in formulating policy and investment portfolio responses to periods of stress.

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Over last few decades, the financial markets around the world have experienced several episodes of financial crises, notably the Latin American crises in 1990s, the Asian crises in late 1990s, and very recently the global financial crisis (GFC). Financial crises often start in one country and spread to others. Such international propagation of a crisis is known as financial contagion. In this dissertation, we define contagion as a significant increase in cross-market co-movements during the crisis period which is above and beyond the co-movement during the pre-crisis period.[1] Theory suggests that interconnected economic fundamentals such as trade and financial linkages among or between the countries can create avenues to transmit a crisis across the borders, and early empirical studies show that countries with weak economic fundamentals are prone to contagion (Kaminsky et al., 1998; Kaminsky and Reinhart, 1998; Kaminsky and Schmukler, 1999; van Rijckeghem and Weder, 2001). The considerable changes in the financial markets over last few decades, due to financial globalization including the removal of restrictions on the cross-border flows of goods and services have been associated with exposure to contagion (Bekaert et al., 2005; Kalemli-Ozcan et al., 2013). However, the mechanisms by which a crisis transmits across borders and constitutes contagion are not well understood. Empirical evidence suggests

[1]See Chapter 2, Section 2 for detail.

limited explanatory power of economic linkages for contagion, and behavioural theories postulate that market idiosyncrasies, often attributed to the behaviour of market participants, play important roles to propagate a crisis internationally (Boyer et al., 2006; Calvo and Mendoza, 2000; Dornbusch et al., 2000; Dungey et al., 2005; Kodres and Pritsker, 2002; Kyle and Xiong, 2001; Moser, 2003; Yuan, 2005).

The GFC of 2007-2009 started in the United States and rapidly spread across global financial markets resulting in a sharp decrease in stock market indices, and a widespread failure of financial institutions. The latter phenomenon refers to a systemic crisis where failure of one or more financial institutions leads to instability of the overall financial system which by then incurs a huge cost, financially and economically, to stabilize the system. The contagious and systemic nature of the crisis has increased the concern about the stability of the financial system and the overall economy. Policy makers around the world introduced a variety of unconventional policy measures such as bailouts, debt and deposit guarantees, liquidity supports and capital injections to stabilize the financial sector and the real economy at large (Ait-Sahalia et al., 2012; Benetrix and Lane, 2015; BIS, 2010; Klyuev et al., 2009; Mishkin, 2011). Although sound economic fundamentals and prudential regulations are preventative measures within the remit of domestic authorities, financial crises transmitted from other jurisdictions present a considerable threat to domestic economies (Kalemli-Ozcan et al., 2013). In this context identifying contagion through all potential channels is important, as contagion through different channels may require different policy prescriptions.[2] Identifying and understanding multiple contagion sources and their contribution to market volatility and amplification of the crisis promote the financial stability, hence, reduce the economic and social costs of a crisis.

[2]For example, economic isolation or quarantining an economy, such as by imposing capital controls, could be appropriate for idiosyncratic shocks as they represent temporary phenomena. However, the same could not be the solution for common shocks as they limit the functioning of the interdependent markets (Rose and Spiegel, 2010).

The existing empirical literature highlights the contagion effects in equity markets during the GFC. Baur (2012) finds that many advanced and emerging equity markets experienced significant contagion effects coming from the global equity market and the global financial sector had significant impact on real economy sectors. Aloui et al. (2011) and Hwang et al. (2013) also find evidence of contagion in emerging markets. Bekaert et al. (2014) and Rose and Spiegel (2010), however, find little evidence of crisis shock effects from the US to other countries during the GFC. Bekaert et al. (2014) find that the impact of the crisis in highly integrated economies is less pronounced than in economies with a lower level of global integration, which is contrary to the *globalization hypothesis* which claims that financial markets with a high level of global integration are affected the most by the crisis (Kalemli-Ozcan et al., 2013). Such contradictory empirical findings in the existing literature provide incentives for further investigation to better understand contagion in global equity markets and have important implications for public policies, portfolio allocation and asset pricing.[3]

This dissertation examines contagion in equity markets around the world during the GFC using a range of econometric approaches and models and provide a significant association between contagion and systemic dimension of a crisis. Our analysis exploits a factor model approach to identify the potential channels by which crisis shocks may transmit internationally and constitute contagion. It is difficult to identify and isolate the explicit economic linkages, and implicit behavioural aspects of contagion empirically. The factor model includes a latent process representing a common factor which explains market interdependence through economic linkages, and the idiosyncratic factor which captures the be-

[3]For example, the policy measures to ease monetary conditions during a crisis emphasise on mitigating the crisis effects channelized through particular mechanisms (see eg Joyce et al. (2012)). Joyce et al. (2012) argue that the implementation of quantitative easing as a response to the GFC was to reduce the crisis effect through portfolio rebalance. In addition, during a crisis, an investor who suffers large losses may reduce her risk by selling assets at the distressed or fire prices. If a fire sale leads to a sharp reduction in the price of an asset, values of similar assets held by other investors may decline leading to a downward spiral in asset prices (Shleifer and Vishny, 2011).

haviour of market participants. In addition, the factor model is flexible enough to incorporate a potential structural shift in the relationship between countries during a crisis period which is above and beyond that accounted for economic linkages (Bekaert et al., 2014; Forbes and Rigobon, 2002), and the volatility spillovers in international financial markets (Chiang and Wang, 2011; Diebold and Yilmaz, 2009; Edwards and Susmel, 2001; Hamao et al., 1990). The approach nests several other empirical approaches for testing contagion (Bae et al., 2003; Baur, 2012; Bekaert et al., 2005, 2014; Corsetti et al., 2005; Dungey et al., 2005, among others).

The first essay of this dissertation, Chapter 2, examines the evidence for contagion from the US equity market to the equity markets of world's largest advanced and emerging economies. While the existing literature on detecting contagion during the GFC largely focuses on advanced economies, we provide a comparative analysis of advanced and emerging economies. We further examine contagion at the financial sector level across the countries; sectoral level analysis is rare in the existing literature. A notable exception is Baur (2012). However, our empirical approach is different from Baur's approach in the sense that his focus is on contagion through observable common factor whereas our focus is on contagion through unobservable idiosyncratic factor. We decompose the market volatility for recipient markets and examine the contribution of contagion to market volatility. As the literature suggests that the financial markets of advanced economies are more integrated and interdependent than that of emerging economies, we hypothesize that the equity markets of advanced countries are more likely to experience contagion compared to the equity markets of emerging economies. We expect the evidence to be more pronounced at financial sectoral level because financial sectors across the world have higher levels of global integration than other sectors, which we hypothesise makes them more vulnerable to contagion.

From an empirical perspective, the conventional approach of measuring contagion focuses on correlation coefficients or beta coefficients, the statistical measures of co-movements and how such parameters change during the crisis period compared to pre-crisis period. The literature suggests that ignoring time varying volatility while estimating such parameters may produce biases (Dungey et al., 2005; Forbes and Rigobon, 2002). Forbes and Rigobon (2002) propose an adjustment in cross-market correlation, considering the increased volatility of the source market during the crisis period. Dungey et al. (2005) indicate that, even with the proposed adjustment, the Forbes and Rigobon (2002) test may fail to detect contagion perhaps due to a structural break or shift in the underlying relationship between the two markets. Dungey and Renault (2013) offer a conditional factor model within a generalized method of moments (GMM) framework which accounts for heteroskedasticity and considers the potential change in structural relationship during the crisis period. Therefore, relaxing the assumption of homoscedasticity in financial data in Chapter 2, we re-examine contagion using the approaches of Forbes and Rigobon (2002) and Dungey and Renault (2013) in Chapter 3. Here, we focus on the contagion through a common factor. Allen and Babus (2009) argue that a crisis may break down the existing network of relationships across the markets. If that is the case, we are most likely to observe a structural break in the common factor exposure across the financial markets during the crisis period.

The global banking markets were hit hard by the crisis. Problems in the subprime mortgage market in the US in 2007 caused significant disruption to the international interbank market. The subsequent failures of Bear Stearns (in March 2008) and Lehman Brothers (in September 2008) amplified the crisis. When the crisis spread globally, the banking systems of many countries experienced a systemic banking crisis. Banking sectors in Europe and emerging markets were affected (Acharya and Schnabl, 2010; Fecht et al., 2012; Kalemli-Ozcan et al., 2012). Fecht et al. (2012) document the extensive external interbank on-balance sheet linkages of banks. Hence, interbank markets are inherently vulnerable to contagion (Iyer and Peydro, 2011; Upper, 2011). The potential for contagion to ignite systemic crises has led to concern amongst policy makers over the risk of contagion and associated threats to financial stability. The resilience of the domestic financial system to a systemic crisis depends not only on the industry characteristics such as bank capital, market concentration and modalities of the banking activities, but also on the crisis shocks (contagion) from outside the domestic system. To address this issue, in Chapter 4, we propose a multifactor model that generalises the linkages across the banking sectors by identifying four possible channels - market interdependence, market idiosyncrasies, structural shift (potentially capturing herd behaviour) and market volatility, and examine which of these four channels were effective in transmitting the crisis in the banking markets around the world during 2007-2009 and specifically account for the contribution of the domestic banking sectors in contributing to a systemic crisis in recipient countries. In doing so we contribute to filling a gap in the literature about the systemic dimension of contagion effects.

One of the important characteristics of international equity markets is that they tend to experience jumps, and that these jumps often occur simultaneously across the markets leading to higher comovements (Das and Uppal, 2004). Such increased comovement between the markets is akin to the definition of financial contagion in the literature. Although the jumps are infrequent events and represent the unexpected arrivals of the news in the markets causing significant price discontinuities, a high degree of correlation of risk of jumps across the markets or assets represents systemic risk (Das and Uppal, 2004). The literature suggests that firms respond differently to market jumps (Todorov and Bollerslev, 2010). In other words, the systematic risk of individual stocks differs when there is a jump in the market returns. Nicolo and Kwast (2002) argue that if systematic risk responses across financial firms move closely together there is inherent systemic risk in the aggregate financial system. The GFC put the spotlight on the systemic risk and systematic risk of financial institutions. The systematic risk or the market risk measures the magnitude of comovement of a firm with respect to the market whereas systemic risk measure the impact of the failure of one firm on the market. Both of these risks are associated with capital regulation (Acharya et al., 2010; Gauthier et al., 2012; Kashyap et al., 2010). More specifically, the systematic risk is more frequently linked with micro-prudential capital regulation, whereas the systemic risk is often associated with macro-prudential capital regulation.

The literature suggests that systematic risk (beta) plays an important role in estimating banks' cost of capital, and therefore lending rates and economic activities (Baker and Wurgler, 2013; Gilchrist et al., 2013; Kashyap et al., 2010; Miles and Ezzell, 1980). But the conventional capital asset pricing model (CAPM) beta does not capture the time-varying nature of systematic risk (Ferson and Harvey, 1993; Jagannathan and Wang, 1996), and is not robust to the price discontinuities or jumps in the market portfolio (Todorov and Bollerslev, 2010).

There is an evolving strand of literature using high frequency financial econometric techniques to identify jumps in the price process and to measure and disentangle systematic risk into systematic continuous risk and systematic jump risk (Alexeev et al., 2014; Barndorff-Nielsen and Shephard, 2004; Lee and Mykland, 2008; Todorov and Bollerslev, 2010). There is also a growing body of literature that examines systemic risk in the financial sector. For example, Acharya et al. (2010) provide a new theoretical framework for measuring systemic risk and Brownlees and Engle (2012) implement this to develop a $SRISK$ index, which captures the vulnerability to the deterioration in equity capital of the financial system. The aggregate $SRISK$ measure also provides early warning signals of distress in the economy. Dungey et al. (2012) also provide an index, $SIFIRank$, for measuring systemic risk based on interconnectedness amongst firms.[4] The

[4]In addition, there are other systemic risk measures such as CoVar proposed by Adrian and Brunnermeier (2011) and CATFIN proposed by Allen et al. (2012). The CATFIN, however, measures the systemic risk at macro level - the banking sector affects the macro-economy through an aggregate lending channel.

literature, however, does not explore how systematic and systemic risks are interrelated. Chapter 5 of this dissertation attempts to fill this gap.

In Chapter 5, we disentangle the systematic risk of large US financial firms into systematic jump risk and systematic continuous risk, and relate systematic jump risk with the empirical measures of systemic risk provided in Brownlees and Engle (2012), and Dungey et al. (2012). More specifically, we first detect jumps in the price process of financial sector index using the conventional approach of Barndorff-Nielsen and Shephard (2006) and measure the contribution of jumps to the financial sector volatility.[5] The literature suggests that the jumps are rare and unexpected events which lead to significant changes in the asset prices. Therefore, we expect few jump events in our sample market portfolio. Second, we estimate financial firms' responses (betas) to continuous and jump components in the market price process. We apply Todorov and Bollerslev (2010) approach to decompose the CAPM beta into continuous beta and jump beta and provide monthly estimates for the sample period. The literature suggests that jumps in market portfolio may yield different systematic risk exposure to the individual stocks; jump beta is larger than continuous beta. Finally, we examine the impact of systemic risk and firm characteristics on jump betas. We use $SRISK$ and $SIFIRank$ as proxies for systemic risk. As $SRISK$ measures the systemic risk based on equity capital and the financial firms with lower equity are more sensitive to market movements, we expect that financial firms with higher $SRISK$ will have higher jump beta. Considering the potential resilience power of interconnected network, we expect that financial firms with higher $SIFIRank$ (less interconnected) will have higher jump beta.

Finally, Chapter 6 summaries the implications of the research findings of this study, presents its limitations and outlines potential avenues for further research. The results imply that policies addressing idiosyncratic shocks and bank capital

[5]See Dumitru and Urga (2012) for comparison of different jump detection methodologies in the literature.

regulation help to reduce the financial and real economic consequences during times of stress. The results for systematic risk imply that market jumps may lead to changes in the systematic risk of financial firms, which may in turn affect their cost of capital and therefore have implications for the bank capital regulation. The results from this dissertation also imply that investors can benefit from international portfolio diversification in emerging markets, even during a crisis period. The within-country idiosyncratic factor explains a large proportion of market volatility in emerging markets, and the correlation coefficients between the US equity market and equity markets of other economies reduce significantly when we adjust for heteroskedasticity in return series during the crisis period.

Chapter 2

Equity Market Contagion during the Global Financial Crisis: Evidence from the World's Eight Largest Economies

2.1 Introduction

The global financial crisis (GFC), which began when the US real estate bubble burst in 2007, quickly led to a sharp decline in stock market indices in the US and across global financial markets – both advanced and emerging. Over the crisis period (from July 2007 to May 2009), the US equity market alone lost about 40 percent of its market capitalization. The loss is even higher for some other countries. For example, the UK equity market lost about 49 percent and the Russian equity market about 52 percent. At a sectoral level, the financial sectors around the world experienced even greater losses (in percentage points). The US financial sector experienced a loss of approximately 60 percent in its market capitalization, the UK financial sector lost about 66 percent, and the Russian financial sector about 70 percent. These facts show the severe impact of the global financial crisis on financial markets around the world. An important question is whether this increased co-movement of global financial markets during the 2007–2009 crisis provides evidence of contagion. Defining contagion as a significant increase in cross-country co-movement of asset returns, we test for the existence of contagion and measure contagion effects running from the US to both advanced and emerging markets. The focus of our analysis is on the aggregate equity market in general and the financial sector in particular.

We take the latent factor approach of Dungey et al. (2005), which nests several other empirical approaches (Bekaert and Harvey, 1995; Forbes and Rigobon, 2002; Corsetti et al., 2005) in a unifying framework to test for contagion. Our sample consists of the US (as a crisis originating country) and eight other large economies in terms of GDP (the four largest advanced economies – France, Germany, Japan and the UK – and the four largest emerging economies – BRIC: Brazil, China, India and Russia). We use a relatively large sample period (daily returns data from 2004 to 2010) and determine crisis and non-crisis periods using an Iterative Cumulative Sum of Squares (ICSS) approach (Inclan and Tiao, 1994; Sanso et al., 2004).

Our results provide strong evidence of contagion effects from the US equity market to equity markets in both advanced and emerging markets. Contagion from the US explains a large portion of the variance in stock returns in advanced and emerging economies. However, the contagion effect is lower in financial sector index than in the aggregate equity market, particularly in advanced economies. The results for the financial sector cast doubt on the financial globalization hypothesis – that is, whether contagion during the crisis has a greater effect on those markets that are highly integrated. Overall, our results are consistent with previous studies on equity market contagion during the GFC (Aloui et al., 2011; Baur, 2012; Bekaert et al., 2014; Hwang et al., 2013). However, unlike Bekaert et al. (2014), we find large contagion effects in equity markets. The literature on cross-country contagion effects measured only in the financial sector is relatively limited. Hasman (2013) provides an overview, pointing out that much of this work is related to the literature on prudential regulation.

The rest of the chapter is organized as follows. Section 2.2 reviews the literature on financial contagion, Section 2.3 explains the latent factor model, sample and data, and empirical model specification, results and discussion are presented in Section 2.4, and Section 2.5 concludes the chapter.

2.2 Literature Review

2.2.1 Defining Financial Contagion

There is no unanimously accepted definition of financial contagion. The definition is closely tied to the statistical definition of how the spread of market disturbances is measured. For example, Eichengreen et al. (1996) define contagion as a significant increase in the probability of a crisis in one country, conditional on a crisis observed in an origin country. Hamao et al. (1990) refer to contagion as a volatility spillover from crisis country to other countries. Forbes and Rigobon (2002) and Dungey et al. (2005), amongst others, refer to contagion as a significant increase in the co-movements of prices across markets conditional on a crisis occurring in one market or a group of markets.

The World Bank summarizes three layers within contagion definitions.[1] In a broad sense, contagion is the cross-country transmission of shocks or the general cross-country spillover effects. In a restrictive sense, contagion is the transmission of shocks to other countries, or the cross-country correlation, beyond any fundamental links amongst the countries and beyond common shocks. In a very restrictive sense, contagion refers to an increase in the cross-country correlations during crisis period relative to the correlations during normal period. The very restrictive definition is commonly used in recent empirical analysis to identify

[1] http://go.worldbank.org/JIBDRK3YC0

and measure financial contagion (Forbes and Rigobon, 2002; Dungey et al., 2005, among others). This chapter follows this convention.

2.2.2 Mechanisms of Crisis Transmission

The literature includes two groups of theories, which are not necessarily mutually exclusive, explaining crisis transmission mechanisms. One group argues that the economic fundamentals of different countries are interconnected by their cross-border flows of goods, services, and capital. When a crisis originates in one country, this interdependence of economies through real and financial linkages becomes a carrier of crisis (Kaminsky and Reinhart, 1998; Glick and Rose, 1999; van Rijckeghem and Weder, 2001). In addition, global phenomena or common shocks such as a major economic shift in industrial countries, significant changes in oil prices, changes in US interest rates, and changes in exchange rates may adversely affect the economic fundamentals of several economies simultaneously, and potentially may cause a crisis (Eichengreen et al., 1996). These fundamental based effects are also known as 'spillovers' (Masson, 1999), 'interdependence' (Forbes and Rigobon, 2002) or 'fundamentals based contagion' (Kaminsky and Reinhart, 1998).

Another group of theories argues that financial crisis spreads from one country to another due to market imperfections or the behaviour of international investors (Diamond and Dybvig, 1983; King and Wadhwani, 1990; Masson, 1999; Dornbusch et al., 2000; Kodres and Pritsker, 2002).Information asymmetries make investors more uncertain about the actual economic fundamentals of a country. A crisis in one country may give a "wake-up call" to international investors to re-assess the risks in other countries, and uninformed or less informed investors may find it difficult to extract the informed signal from the falling price and follow the strategies of better informed investors, generating excess co-movements across the markets (Calvo and Mendoza, 2000; Goldstein, 1998; Pasquariello, 2007; Yuan, 2005). The degree of anticipation of a crisis by investors is crucial for the existence of contagion because of investors' attention allocation (Mondria and Quintana-Domeque, 2012). Sudden shifts in market confidence and expectations have been identified as important factors in causing contagion (Masson, 1999; Mondria and Quintana-Domeque, 2012).

The initial empirical literature on financial crisis and contagion focused on fundamentals based mechanisms and was directed towards developing early warning systems (Eichengreen et al., 1996; Kaminsky et al., 1998; van Rijckeghem and Weder, 2001), while later empirical works are focused on investor behavior-based mechanisms (Dungey et al., 2005; Bekaert et al., 2014).

In an early and influential study, King and Wadhwani (1990) examine the correlation between the US, UK and Japanese stock markets during 1987–1988 (a stock market crash occurred in 1987). They find evidence of increased correlation between the US, UK, and Japanese stock markets during the 1987 crisis which cannot be explained by economic fundamentals. Baig and Goldfajn (1999) use a similar approach to examine financial contagion in Asian markets during the Asian crisis and find that the correlation across the countries for the same asset class (stock markets, interest rates, sovereign bond spreads and exchange rates) increased significantly during the crisis period.

In a seminal paper, Forbes and Rigobon (2002) provide a breakthrough on the conventional correlation analysis approach for testing contagion. As volatility increases during a crisis, an increase in correlation may simply be a continuation of strong transmission mechanisms that exist in more stable periods. Forbes and Rigobon (2002) offer an adjusted correlation coefficient approach to test for contagion in 28 stock markets and three episodes of crisis. They conclude that the observed increase in correlation during crisis period is due to increased interdependence amongst the markets, not contagion.

In a slightly different fashion, Dungey and Martin (2001); Bekaert et al. (2005); Corsetti et al. (2005); Bekaert et al. (2014), amongst others, follow a factor model of correlation analysis to test for contagion during different episodes of financial crises.

There is a growing body of empirical literature testing for financial contagion during the GFC. Using a broad set of data from 55 advanced and emerging countries, Bekaert et al. (2014) examine the transmission of crises to country-industry equity portfolios in 55 countries during the global financial crisis. Using a CAPM-based approach, they find systematic and substantial contagion from domestic equity markets to individual domestic equity portfolios, with its severity inversely related to the quality of countries' economic fundamentals. They find limited evidence of contagion running from US markets and from the global financial sector, and conclude that investors focus substantially more on country-specific characteristics (idiosyncratic risks) during the crisis period. However, in a slightly different empirical setting, Baur (2012) uses sectoral level data from 25 countries (advanced and emerging) and examines the spread of financial crises from the financial sector to the real sector within a country and across countries during the crisis. He finds strong contagion effects and claims that no region or specific group of countries has been immune to shocks associated with crisis; however, real economy sectors, especially healthcare, telecommunication and the IT sector, were less affected by contagion.

The existing literature on detecting contagion during the GFC consistently finds evidence for significant contagion effects. However, only a few papers consider evidence for the BRIC countries. Kenourgios et al. (2011) find contagion between the BRIC countries, the US and the UK for 5 historical crisis events using weekly data. Hwang et al. (2013) find evidence of contagion for China, Russia and India (but omit Brazil from their study). On the other hand, Samarakoon (2011) finds no evidence of contagion from the US to China or Russia in the GFC, and shows that in the case of India shocks from the US exacerbated the difference between US and Indian returns (that is, contagion operated in the opposite direction than expected). The author finds identifiable contagion effects only for Brazil and in general concludes that the evidence is stronger for contagion to Latin America than other markets. The US–Brazil contagion linkage is also strongest in Aloui et al. (2011). The authors also find that the commonality between the US and Brazil and the US and Russia is stronger than that for the US and China and the US and India.

A stylized fact of the GFC is that financial markets around the world suffered from tremendous losses. However, there remains disagreement on the international transmission of the crisis and its mechanisms; in particular, whether the international transmission of the crisis resulted from interconnected global markets (through real and financial linkages) or was caused by idiosyncratic factors (attributed to behaviours of market participants during the crisis period). The divergent empirical findings on contagion tests largely depend on how the crisis transmission channel is defined and how it is implemented in an empirical setting (Dungey et al., 2005). The detection of contagion effects requires a formal definition and measurement of the underlying shocks. A number of approaches suggest that contagion is evident only in the tail (or extreme) events of market returns. In this case they may, for example, look for the coincidence of tail returns across different markets or assets, as done by Bae et al. (2003) or Boyson et al. (2010), or for the effects of outliers in one market on those in another as in Favero and Giavazzi (2002). Proponents of the non-linear nature of contagion effects support mechanisms such as copula, DCC or GARCH frameworks (Aloui et al., 2011; Busetti and Harvey, 2011; Caporin et al., 2013; Hwang et al., 2013; Kenourgios et al., 2011). Dungey et al. (2005) show how a latent factor model of the entire sample nests the coincident tail and outlier approaches. At the present time there is no literature showing the dominance or otherwise of the copula approach relative to other methods. Caporin et al. (2013) do not find any evidence that the quantile approach results in a different outcome to that obtained from the entire distribution.

2.3 The Empirical Framework

2.3.1 The Latent Factor Model

The latent factor model is based on the Capital Assets Pricing Model (CAPM) framework. Let the return on an asset, $y_{i,t}$, during the non-crisis period be a function of a common factor, w_t, which affects all the asset markets, and an idiosyncratic factor, $u_{i,t}$, which is specific to a particular asset market. The relationship can be expressed as:

$$y_{i,t} = \lambda_i w_t + \delta_i u_{i,t};\ i = 1, 2, ..., N \tag{2.1}$$

where i refers to the market i, and t refers to time. The λ_i and δ_i refer to factor loadings of common factor and idiosyncratic factors, respectively. The factors are assumed to be latent stochastic processes with zero mean and unit variance. The factors are orthogonal to each other, and the covariance of idiosyncratic factors across different markets is assumed to be zero:

$$w_t \sim i.i.d.(0, 1) \tag{2.2}$$

$$u_{i,t} \sim i.i.d.(0, 1) \tag{2.3}$$

$$E[w_t u_{i,t}] = 0\, \forall i \tag{2.4}$$

$$E[u_{i,t} u_{j,t}] = 0\, \forall i \neq j. \tag{2.5}$$

Therefore, for the pre-crisis period, the unconditional variance and covariance of $y_{i,t}$ can be expressed as:

$$E[y_i^2] = \lambda_i^2 + \delta_i^2\ (i = 1, 2, ...N) \tag{2.6}$$

$$E[y_i, y_j] = \lambda_i \lambda_j\ (i = 1, 2, ...N)\ \forall i \neq j, \tag{2.7}$$

Assume that a crisis originates in the first market via an idiosyncratic shock. During the crisis period, the idiosyncratic factor of the first market may affect the returns on assets in other markets in a way which does not occur during the non-crisis period. This avenue is identified as a contagion channel. Therefore, during the crisis period, the return on assets in each market can be expressed as:

$$y_{1,t} = \lambda_1 w_t + \delta_1 u_{1,t} \tag{2.8}$$

$$y_{j,t} = \lambda_j w_t + \delta_j u_{2,t} + \varphi_{j,1} u_{1,t};\ j = 2, ..., N. \tag{2.9}$$

That is, the potential effect of shocks which originated in the first market (the US in our context) on other markets during the crisis period is given by the parameter $\varphi_{j,1}$, and a test of whether $\varphi_{j,1} = 0$ will be a test against the null of no contagion.

If we allow contemporaneous shocks across the markets, then Eq. (2.8) and (2.9) can be expressed as:

$$y_{i,t} = \lambda_i w_t + \delta_i u_{i,t} + \sum_{i=1,i\neq j}^{N} \varphi_{i,j} u_{j,t};\ i = 1, ..., N. \tag{2.10}$$

Now the test of contagion relies on the statistical significance of the $\varphi_{i,j}$s.

For the crisis period, as in Eq. (2.6), the variance of $y_{i,t}$, based on Eq. (2.10) can be expressed as:

$$E[y_i^2] = \lambda_j^2 + \delta_i^2 + \sum_{i=1,i\neq j}^{N} \varphi_{i,j}^2\,(i = 1, 2, ...N)\,. \tag{2.11}$$

The contribution of each factor can be represented as the proportion of volatility of y_i explained by common shocks, idiosyncratic factor and contagion respectively:

$$\frac{\lambda_i^2}{\lambda_i^2 + \delta_i^2 + \sum_{j=1,j\neq i}^{N} \varphi_{i,j}^2};\ \frac{\delta_i^2}{\lambda_i^2 + \delta_i^2 + \sum_{i=1,i\neq j}^{N} \varphi_{i,j}^2};\ \frac{\varphi_{i,j}^2}{\lambda_i^2 + \delta_i^2 + \sum_{i=1,i\neq j}^{N} \varphi_{i,j}^2}. \tag{2.12}$$

Eq. (2.12) provides the descriptive measure of the relative strength of contagion in contributing to the volatility of returns during the crisis period. In this way the latent factor approach of Dungey et al. (2005) provides not only a test for contagion but also a measure of the relative strength of contagion explaining market volatility.

2.3.2 Sample and Data

Along with the US as the crisis origin country, we focus on four major advanced economies (France, Germany, Japan and the UK) and four major emerging economies (BRIC: Brazil, Russia, India and China) to examine the international transmission of the crisis. The selection of these countries is based on their size (in terms of gross domestic product, GDP) and their economic/market structure. The five advanced economies are the largest five countries from the advanced economy group and the four emerging economies are the largest four countries from the emerging economy group as classified by International Monetary Fund.[2] These nine markets together make up about 62.1 percent of world GDP (authors' calculation based on 2010 GDP in current US dollars).[3]

Our sample period covers from January 02, 2004 to December 31, 2010. Following (Dungey et al., 2005) and Forbes and Rigobon (2002), we use daily data for aggregate equity market index and financial sector index, extracted from Thompson Reuters Datastream and compute daily returns as the log difference of the daily price index. To overcome the geographical time differences problem (amongst the sample economies), we use Day 01 in US and Brazil = Day 02 in European and Asian markets markets. We also performed sensitivity analysis by using a two-day moving average (as in Forbes and Rigobon (2002)), as well as data without time adjustment. The results are robust to these changes.

[2] http://www.imf.org/external/pubs/ft/weo/2010/02/weodata/weoselgr.aspx, accessed on 15/04/2012.

[3] http://data.worldbank.org/indicator/NY.GDP.MKTP.CD, accessed on 15/04/2012.

2.3.3 Identifying Crisis Dates

The empirical literature on financial contagion suggests that the results are sensitive to the data windows and choice of crisis date (Dungey et al., 2005). Correlation based studies often rely on exogenously determined crisis dates. In this chapter, we use endogenously determined crisis and non-crisis periods. We use an Iterative Cumulative Sum of Square (ICSS) algorithm based on the CUSUM test to detect the structural change in variance of an individual return series (Inclan and Tiao, 1994; Sanso et al., 2004) and first applied to crisis period detection by Wang and Nguyen Thi (2012).

The ICSS approach assumes that return series exhibit a stationary variance over an initial period until a sudden change in variance occurs and then becomes stationary again for a time until the next sudden change. This process is repeated through time, yielding a number of changes in the variance(Aggarwal et al., 1999). Consider the demeaned asset return series, ε_t, which is normally distributed with σ_t^2. For the whole sample of T observations, the variance within each interval is denoted by $\tau_j^2, j = 0, 1, ...N_T$, and $1 < k_1 < k_2 < ... < k_{N_T} < T$ are the dates of break in variance,

$$\begin{aligned} \sigma_t^2 &= \tau_0^2;\ if\ \ 1 < t < k_1, \\ &= \tau_1^2;\ if\ \ k_1 < t < k_2, \\ &\qquad\cdots \\ &= \tau_{N_T}^2;\ if\ \ k_{N_T} < t < T. \end{aligned} \tag{2.13}$$

To estimate the number of changes in variance and the point in time of each variance shift Inclan and Tiao (1994) define a D_k statistic as follows:

$$D_k = \frac{C_k}{C_T} - \frac{k}{T}; \quad k = 1, ..., T \ \ |D_0 = D_t = 0 \tag{2.14}$$

where, $C_k = \sum_{t=1}^{k} \epsilon_t^2,\ k = 1, ..., T$ is the cumulative sums of squares of ϵ_t from the beginning of the series to k^{th} point in time. If there are no changes in variance over the sample period, the D_k statistic oscillates around zero and asymptotically, be-

Table 2.1: Structural breaks in the US equity and financial index returns

SN	Description	Aggregate equity index	Financial sector index	Remarks
1	First break	July 19, 2007	July 19, 2007	Crisis period begins
2	Second break	September 12, 2008	July 4, 2008	Heightened period
3	Third break	June 1, 2009	May 29, 2009	Crisis period ends
4	Fourth break	September 3, 2010	December 12, 2010	Post crisis period ends

haves as a standard Brownian motion (Inclan and Tiao, 1994).[4] If there is one or more sudden variance changes in the series, the D_k values drift either up or down from zero (Aggarwal et al., 1999). Sanso et al. (2004) offer modifications to the ICSS algorithm incorporating heteroskedasticity and fourth moment properties of financial data and replace D_k by $G_k = \tilde{\omega_4}(C_k - \frac{k}{T}C_T)$, where $\tilde{\omega_4}$ is a consistent estimator of ω_4, the long-run fourth moment of ϵ_t (Sanso et al., 2004).[5] The null hypothesis of no break in variance is rejected when $G_{k^*} = Max_k(|T^{-0.5}G_k|)$ is outside the confidence interval range. The simulation based critical value (at α=5%) for G_{k^*} is 1.406.

Table 2.1 provides the results for the ICSS test to our sample. The break dates are approximately equivalent to GFC period defined by the World Bank (BIS, 2009) and the US recession end date defined by the National Bureau of Economic Research (NBER, 2010). Since the crisis began in the financial sector, we choose the financial sector break dates. Therefore the crisis period considered in this chapter is from July 19, 2007 to May 29, 2009.

2.3.4 Stylized Facts and Descriptive Statistics

Unlike previous financial crises, such as the Mexican crisis of 1994 and the Asian crisis of 1997– 1998, which were often regional in nature and lasted for a relatively

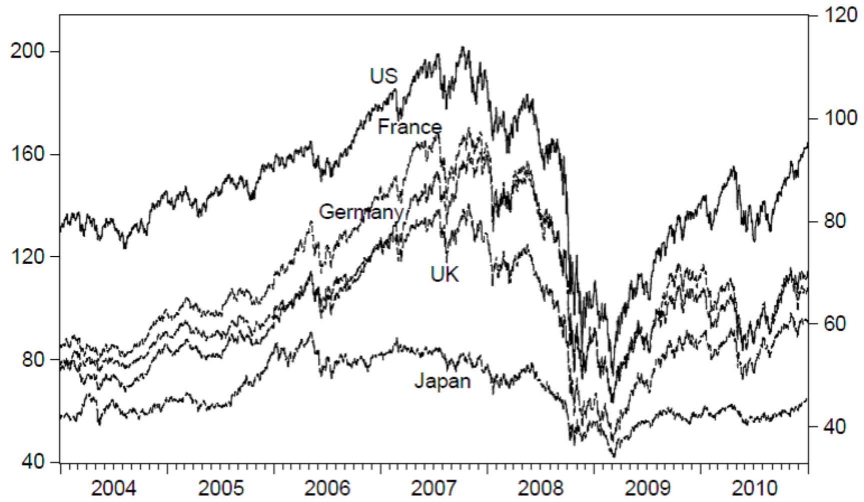
[4]This can be observed by plotting $D_k$values against k.

[5]The non-parametric estimator of ω_4 is:

$$\tilde{\omega} = \frac{1}{T}\textstyle\sum_{t=1}^{T}(\epsilon_t^2 - \tilde{\sigma}^2)^2 + \frac{2}{T}(\sum_{l=1}^{m}\omega(\iota,\omega)\sum_{t=l+1}^{T}(\epsilon_t^2 - \tilde{\sigma}^2)^2(\epsilon_{t-l}^2 - \tilde{\sigma}^2)^2 \tag{2.15}$$

where $\omega(\iota,\omega)$is a Bartlett window and $\tilde{\omega_4}$ estimate depends on the choice of m parameter with the Newey-West method (Sanso et al., 2004).

Figure 2.1: Aggregate equity market price index for advanced countries

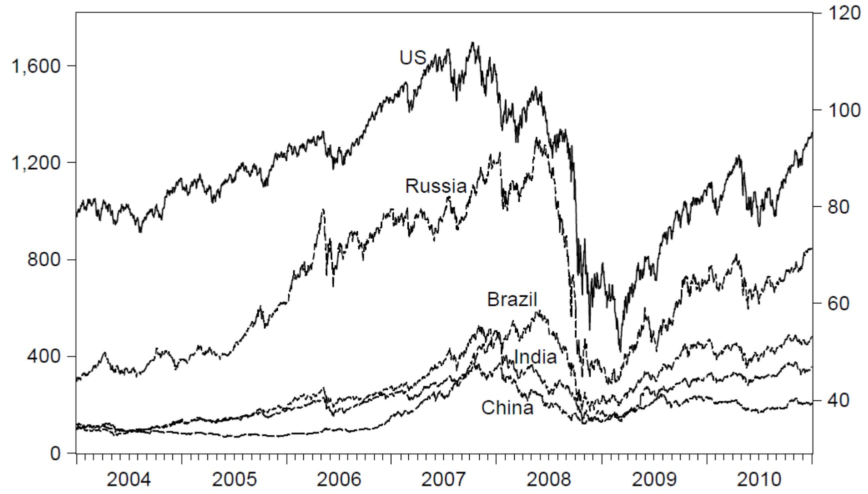


Note: The right hand side scale applies to US and left hand side scale applies to rest. The price index is measured in US dollars and re-indexed to 100 on January 1, 2000. *Data source:* Thompson Reuters Datastream.

short period of time, the GFC lasted for about two years. This crisis affected both the advanced economies and the emerging economies in our sample. As revealed in Figure 2.1 and 2.2, before the crisis, the equity market indices of these economies were increasing gradually. When the crisis hit over the period from July 2007 to May 2009, the US equity market alone lost about 40 percent of its market capitalization, the French equity market lost about 46 percent, the German equity market about 41 percent, the Japanese equity market about 35 percent, and the UK equity market about 49 percent. The magnitude of the crisis effect in emerging markets, however, is relatively low. For example, China, India, and Brazil lost equity market capitalization by about 23, 24, and 25 percent, respectively. The Russian equity market lost the most at about 52 percent.

The effect of the crisis is more severe in the financial sector. The US financial sector lost about 60 percent of market capitalization, whereas the French, German, and Japanese financial sectors lost about 58 percent, 50 percent and 45 percent, respectively, and the UK financial sector experienced the highest loss (about 66 percent) amongst the advanced economies. The loss figures for the financial sector are about 10–20 percent above the loss in the overall equity

Figure 2.2: Aggregate equity market price index for emerging countries and the US



Note: The right hand side scale applies to US and left hand side scale applies to rest. The price index is measured in US dollars and re-indexed to 100 on January 1, 2000. *Data source:* Thompson Reuters Datastream.

markets for each country. In the case of emerging economies, except for Russia, the loss faced by the financial sector is about 30 percent. The Russian financial sector experienced an approximate 70 percent loss in its market capitalization during the global financial crisis, which is the highest loss amongst all the markets investigated. All these markets experienced negative returns over the crisis period, and their market volatility (standard deviation) approximately doubled compared with the non-crisis period. US financial sector volatility increased by approximately fourfold. These facts indicate the severity of this crisis.

The descriptive statistics in Table 2.2 reveal that while emerging markets experienced relatively lower negative returns than advanced markets during the crisis period, emerging markets were relatively more volatile than advanced markets at the same time. During the non-crisis period, the emerging markets had higher returns than the advanced markets. Furthermore, in the advanced economies, the overall equity market portfolio has higher returns than the financial sector portfolio, whereas in the emerging markets, the financial sector portfolio has higher returns than the aggregate equity market portfolio. The higher performance of

Table 2.2: Descriptive statistics

	Advanced Markets					Emerging Markets			
Panel A: Equity market index returns									
Crisis period (19 July 2007 to 29 May 2009, n =487)									
Statistics	US	France	Germany	Japan	UK	Brazil	China	India	Russia
Mean	-0.103	-0.118	-0.102	-0.087	-0.127	-0.049	-0.043	-0.032	-0.117
Median	0.000	-0.040	0.010	0.000	0.000	0.052	0.000	0.000	0.000
Maximum	10.902	10.647	16.262	10.418	11.817	14.036	9.024	18.135	23.286
Minimum	-9.409	-10.694	-8.622	-8.733	-10.390	-16.224	-8.060	-12.440	-21.057
Std. Dev.	2.205	2.308	2.182	2.025	2.466	3.320	2.455	2.794	3.594
Non crisis period (02 Jan. 2004 to 30 Dec. 2010 excluding crisis period, n = 1338)									
Mean	0.052	0.060	0.067	0.041	0.061	0.138	0.069	0.094	0.121
Median	0.066	0.071	0.124	0.000	0.068	0.205	0.037	0.188	0.177
Maximum	4.327	9.475	5.575	4.092	7.313	6.910	8.044	7.802	9.535
Minimum	-4.026	-5.203	-4.401	-7.508	-4.857	-7.918	-9.151	-12.485	-10.813
Std. Dev.	0.822	1.168	1.108	1.135	1.062	1.641	1.543	1.536	1.929
Panel B: Financial sector index returns									
Crisis period									
Mean	-0.189	-0.173	-0.136	-0.121	-0.211	-0.074	-0.050	-0.062	-0.218
Median	-0.248	-0.169	-0.091	0.000	-0.269	-0.113	0.000	0.000	-0.047
Maximum	13.507	14.972	12.665	12.611	16.265	16.946	9.521	21.515	28.402
Minimum	-16.283	-11.640	-11.068	-11.778	-13.118	-18.384	-8.905	-15.860	-23.498
Std. Dev.	3.772	3.160	2.599	2.795	3.390	3.446	2.684	3.659	4.277
Non crisis period									
Mean	0.041	0.060	0.051	0.028	0.047	0.170	0.077	0.117	0.254
Median	0.025	0.070	0.087	0.000	0.056	0.188	0.000	0.150	0.150
Maximum	5.420	16.037	7.106	6.482	10.268	7.569	7.525	11.558	12.581
Minimum	-5.081	-7.275	-4.765	-10.008	-6.110	-8.637	-8.688	-14.099	-12.412
Std. Dev.	1.041	1.483	1.166	1.459	1.250	1.814	1.733	1.891	2.393

the financial sector in emerging markets could be attributed to banking-oriented capital markets, less market competition, and higher economic growth in these economies.

2.3.5 Empirical Model Specifications

Our empirical setting relies on the factor model specification of Dungey et al. (2005) as shown in Eq. (2.8) and (2.9). The crisis first originated in the US market and subsequently spread to other markets. We examine US contagion effects in advanced economies and emerging economies separately to achieve exact identification. In a five markets case, there are 15 moment conditions. We have five λs and five δs. Therefore, we have a maximum of five contagion channels which be identified with the model. In the actual empirical setting, we define four contagion channels from the US to each of four other countries and we use one additional parameter to check for a structural break in the US common factor. Therefore, our empirical framework proceeds as follows:

$$
\begin{bmatrix} y_{US,t} \\ y_{2,t} \\ y_{3,t} \\ y_{4,t} \\ y_{5,t} \end{bmatrix} = \underbrace{\begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \lambda_3 \\ \lambda_4 \\ \lambda_5 \end{bmatrix} \begin{bmatrix} w_t \end{bmatrix}}_{Common} + \underbrace{diag \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \end{bmatrix} \begin{bmatrix} u_{1,t} \\ u_{2,t} \\ u_{3,t} \\ u_{4,t} \\ u_{5,t} \end{bmatrix}}_{Idiosyncratic}
$$

$$
+ \underbrace{\begin{bmatrix} 0 & & & & \\ \varphi_{12} & 0 & & & \\ \varphi_{13} & & 0 & & \\ \varphi_{14} & & & 0 & \\ \varphi_{15} & & & & 0 \end{bmatrix} \begin{bmatrix} I_t u_{1,t} \\ I_t u_{2,t} \\ I_t u_{3,t} \\ I_t u_{4,t} \\ I_t u_{5,t} \end{bmatrix}}_{Contagion} + \underbrace{\begin{bmatrix} \lambda_0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} I_t w_t \end{bmatrix}}_{Break\ in\ Common} \qquad (2.16)
$$

where I is an indicator function that takes value 1 during the crisis period, otherwise 0. The loading matrix for the idiosyncratic factor in Eq. (2.16) can be altered for the possible contagion channels across the markets including feedback to the US market but the choice of contagion channel is limited by number of available moment conditions and number of parameters to be estimated.[6] We use the generalized method of moments (GMM) approach to estimate the parameters in Eq. (2.16), matching the theoretical and empirical moment conditions.

For the non-crisis period, the variance-covariance structures of markets take the same form as in Eq. (2.4) and (2.5). For the crisis period, the variance-covariance structure of markets can be expressed as:

Variance of the US market:

$$E[y_{US}^2] = \lambda_1^2 + \delta_1^2 + \lambda_0^2. \tag{2.17}$$

Variance of other markets:

$$E[y_i^2] = \lambda_i^2 + \delta_i^2 + \varphi_{1i}^2; \quad i = 2, ..., 5 \neq US. \tag{2.18}$$

Covariance between the US and each of other markets :

$$E[y_{US}, y_i] = \lambda_1\lambda_i + \delta_1\varphi_{1i}; \quad = 2, ..., 5 \neq US. \tag{2.19}$$

Covariance between other markets:

$$E[y_i, y_j] = \lambda_i\lambda_j + \varphi_{1i}\varphi_{1j}; \quad i = 2, ..., 5 \, \forall i \neq j \neq US. \tag{2.20}$$

The non-crisis and crisis period variance-covariance conditions can be obtained by introducing indicator function (I) in Eq. (2.17) to (2.20) as indicated in Eq. (2.16).

We decompose the variance of each market as a proportion contribution of each factor in Eq. (2.16) as specified in Eq. (2.12), (2.17) and (2.18). More specif-

[6] Our preliminary analysis of Granger Causality tests indicates that the US market is not Granger caused by other markets.

ically, for the non-crisis period, the proportion contributed by common factor for each market (i) is given by:

$$\lambda_i^2/(\lambda_i^2 + \delta_i^2) \tag{2.21}$$

and the proportion contributed by idiosyncratic factor is given by:

$$\delta_i^2/(\lambda_i^2 + \delta_i^2). \tag{2.22}$$

For the crisis period, for the US, the proportion contributed by common factor is given by:

$$(\lambda_1^2 + \lambda_0^2)/[(\lambda_1^2 + \lambda_0^2) + \delta_1^2] \tag{2.23}$$

and the proportion contributed by idiosyncratic factor is given by:

$$\delta_1^2/[(\lambda_1^2 + \lambda_0^2) + \delta_1^2]. \tag{2.24}$$

For other markets, the proportion contributed by common factor is given by:

$$\lambda_i^2/(\lambda_i^2 + \delta_i^2 + \varphi_{1,i}^2); \;\; i = 2, ..., 5 \, \forall i \neq US \tag{2.25}$$

the proportion contributed by idiosyncratic factor is given by:

$$\delta_i^2/(\lambda_i^2 + \delta_i^2 + \varphi_{1,i}^2) \tag{2.26}$$

and the proportion contributed by contagion factor is given by:

$$\varphi_{1,i}^2/(\lambda_i^2 + \delta_i^2 + \varphi_{1,i}^2). \tag{2.27}$$

The variance decomposition outlined above provides the relative strength of each factor for a given market contributing to its market volatility.

We test the overall significance of the model specified in Eq. (2.16) using Hansen's J-test for a number of overidentification restrictions where the J-statistic is:

$$J = TQ \tag{2.28}$$

where T is the sample size, and Q is the value of objective value function of the GMM estimator which takes of the form:

$$Q = M'W^{-1}M \tag{2.29}$$

where M is a vector containing the difference between the empirical and theoretical moments and W is the optimal weighting matrix. The J-statistic is distributed asymptotically χ^2 with ϑ (number of restricted parameters) degrees of freedom. Under the null hypothesis, the restrictions are set to be zero. If the value of J statistic is below the χ^2 critical value at 5 percent level of significance for given level of degrees of freedom, the null hypothesis of "the model is valid with restrictions" is accepted.

For a joint test of contagion using factor model in Eq. (2.16), we perform an LR test with 4 degrees of freedom under the null hypothesis ($\varphi_{1,j} = 0$). This test of contagion can be interpreted as testing for changes in both variances and covariances (Dungey et al., 2005).

2.4 Results

2.4.1 Model Restrictions and Statistical Significance

The model in Eq. (2.16) is exactly identified with 15 parameters and 15 moment conditions. The framework allows for a single common factor, w_t, across all the assets, and this single time-varying factor is maintained across both the non-crisis and crisis sample. To verify this specification we apply a Hall (2005, p.175)

Table 2.3: Structural break test (Hall, 2005, p. 178)

Market	France	Germany	Japan	UK	Brazil	China	India	Russia
Panel A: Test for a single factor across both period								
Aggregate equity market index								
$\chi^2_{(48)}$	0.314	0.516	0.128	0.304	0.300	0.262	0.308	0.311
p-value	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Financial sector index								
$\chi^2_{(48)}$	0.249	0.343	0.133	0.219	0.248	0.401	0.336	0.297
p-value	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Panel B: Test for a change in factor loadings								
Aggregate equity market index								
$\chi^2_{(6)}$	81.809	69.150	54.563	92.556	57.595	49.385	56.025	33.281
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Financial sector index								
$\chi^2_{(6)}$	79.489	68.540	53.212	98.500	46.775	34.498	36.118	36.219
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

structural break test against the null of the single factor specification, shown in Table 2.3. The test accepts the null that there is a single factor specification across the two periods. A Hall test against the null of no change in the factor loadings, however, is rejected for all of our markets, supporting our specification of a single common factor across both periods, but allowing for changing parameter loadings in the non-crisis and crisis periods.[7]

We further test the model by imposing restrictions on (i) contagion parameters and parameter for a break in the US common factor, ($\varphi_{1,j} = \lambda_0 = 0$); (ii) parameter for a break in the US common factor ($\lambda_0 = 0$) only; and (iii) contagion parameters, ($\varphi_{1,j} = 0$) only. We used Hansen's J-test for overidentification when restrictions were imposed. The results are reported in Panel A of Table 2.4.

The restrictions $\varphi_{1,j} = \lambda_0 = 0$ is rejected. However, the restriction $\lambda_0 = 0$ is rejected only for models for advanced economies. The hypothesis is not rejected for emerging economies. The statistical significance of the model with a break in the US common factor for advanced economies indicates a shift in the interdependence amongst advanced markets during the crisis. This is not the

[7] As supporting evidence we also conducted the Ghysels and Hall (1990) test of structural change, where the null is that neither the model specification nor the parameter loadings have changed between the two periods. This null is also rejected.

Table 2.4: Model restrictions and statistical significance

Model Restrictions		Advanced Equity	Advanced Financial	Emerging Equity	Emerging Financial
Panel A: J-test for overidentification					
Unconstrained model	J-stat	5.17	1.52	1.87	0.02
Model with restrictions (i)	J-stat	45.98	56.88	51.91	39.49
($\varphi_{1,j} = 0,\ \lambda_0 = 0$)	dof	5	5	5	5
Model with restrictions (ii)	J-stat	6.16	8.17	1.87	0.03
($\lambda_0 = 0$)	dof	1	1	1	1
Model with restrictions (iii)	J-stat	45.98	56.89	51.91	39.49
($\varphi_{1,j} = 0$)	dof	4	4	4	4
Panel B: LR test for models comparison					
Model constrains ($\varphi_{1,j} = 0$)	LR-stat	81.62	110.73	100.08	78.93
	dof	4	4	4	4

Note: In J-test, H_0 : the model with restriction is valid.
At $\alpha = 5\%$, $\chi^2_{(1)} = 5.024$; $\chi^2_{(4)} = 11.14$; $\chi^2_{(5)} = 12.83$; and $\chi^2_{(10)} = 20.48$

case with emerging markets, where we do not find changes in interdependence.

The restriction $\varphi_{1,j} = 0$ is rejected. This test suggests that model estimation without contagion parameters may suffer from misspecification. As this test also approximates the test for a joint hypothesis of no contagion, the rejection of the null hypothesis suggests evidence of significant contagion running from the US to other markets during the global financial crisis. When a formal LR test is performed for a joint test of statistical significance of the contagion parameter estimates ($\varphi_{1,j} = 0$) in Eq. (2.16), we reject the null hypothesis providing statistical evidence of financial contagion in advanced and emerging markets (running from the US market) during the GFC. The result is reported in Panel B of Table 2.3.

2.4.2 Measuring Contagion Effects - Volatility Decomposition

The unconditional volatility decomposition estimates for total equity market returns from the latent factor model for the US and the four advanced and four emerging economies are presented in Table 2.5. During the non-crisis period, the common factor explains a large portion of equity market volatility for ad-

Table 2.5: Unconditional volatility decomposition of aggregate equity market returns (contribution to total volatility, in percent)

Country	Crisis Period Common Factor	Crisis Period Idiosyncratic Factor	Crisis Period Contagion from US	Non-crisis Period Common Factor	Non-crisis Period Idiosyncratic Factor
Panel A: Contagion Effect from US to Advanced Economies					
US	54.25	45.75		37.22	62.78
France	26.74	0.70	72.55	97.44	2.56
Germany	17.41	5.98	76.61	74.44	25.56
Japan	27.07	53.79	19.15	33.48	66.52
UK	27.35	7.51	65.14	78.46	21.54
Panel B: Contagion Effect from US to Emerging Economies					
US	60.82	39.18		59.62	40.38
Brazil	53.36	25.39	21.24	67.76	32.24
China	0.67	70.77	28.57	0.94	99.06
India	0.01	14.56	85.43	0.03	99.97
Russia	0.73	42.63	56.64	1.67	98.33

vanced economies, particularly amongst the European countries. This could be due to the fact that the European countries have similar institutional frameworks to the European Union and therefore markets are more integrated. The results for the crisis period show that the common factor accounts for about 54 percent of the US equity market, about 27 percent (each) of the French, Japanese and British equity markets, and about 17 percent for the German equity market. The country-specific idiosyncratic factors contribute less to the volatility (except for Japan), suggesting less benefit from portfolio diversification for international investors.

During the crisis period, contagion factors are dominant in explaining the volatility of the French, German and British equity markets. The contagion effects running from the US alone explain about 73 percent of the volatility of the French, 77 percent of the volatility of the German and 65 percent of the volatility of the British equity markets. The greater contagion effects in European equity markets can be attributed to panic amongst investors about the effect of the US crisis (in terms of size and influences) on European markets.

Amongst the advanced countries, the Japanese equity market experienced the least contagion effects from the US equity market (US shocks explain about 19 percent of the volatility of the Japanese equity market). Wei (2009) argues that during the crisis period Japanese markets were facing economic problems and a natural disaster (typhoon) and the Japanese media were focusing on those issues rather than the crisis in the US. Within-country attention in Japanese markets is also reflected in the contribution of the country-specific idiosyncratic factor to total equity market volatility (the idiosyncratic factor explains about 54 percent of the volatility of the Japanese equity market).

In the case of emerging markets, the common factor accounts for much less observed volatility in these markets, except Brazil. The emerging markets investigated in general have very different institutional settings, which may contribute to lower commonality in terms of equity market returns. However, in the case of Brazil, there is a relatively high degree of commonality with the US, at almost 68 percent in the non-crisis period and 53 percent in the crisis period. Unlike the other BRICs, the US and Brazil share a common region, which may account for some of this aspect. During the crisis period, the contribution of idiosyncratic shocks from the US to Brazilian volatility accounts for some 21 percent of observed volatility, where these represent transmissions that are statistically differentiated from those due to the commonality already accounted for in the model. The difference in results between the US and Brazil from the other BRICs is also supported by Aloui et al. (2011), who find a strong, symmetric tail dependence between the US and Brazil, but relatively little between the US and Russia, India and China. Aloui et al. (2011) also find that the linkages between the US and Brazil and the US and Russia are stronger than those between the US and China and the US and India, which is consistent with our results, although our Russian evidence is less compelling than in their paper. Dungey et al. (2011) also found evidence of contagion to Russia and Brazil in earlier crises.

The results for contagion effects from the US equity markets to emerging markets indicate that Brazilian and Chinese equity markets experience lower contagion effects from the US than other emerging markets in our sample. The US shocks explain about 21 and 29 percent of the volatility of these markets respectively. The Chinese equity market is well-known to be less globally integrated than others in our study. Wang and Di Iorio (2007) support this, while Girardin and Liu (2007), for example, show that post-1996, the Chinese equity market is less integrated with the US than previously due to the rise of its relationship with the Hang Seng. When a market is not well integrated this supports a high idiosyncratic factor in the results – which is exactly what we see for China. Given that this is evidence of a new international sensitivity in a relatively closed market, it does not seem an unexpected result that the contagion component in China should be lower than in other countries.

Our results also show that US shocks explain about 57 percent of the Russian market volatility. Hwang et al. (2013) also find evidence for linkages between the US and Russia, although they classify these as herding behaviour, which they characterize as a precursor to contagion. In contrast with the results in Aloui et al. (2011), but supported by Hwang et al. (2013), the evidence for contagion effects to India is relatively strong.

The country-specific idiosyncratic shocks explain a large portion of the volatility of these markets, in particular the Chinese and Russian equity markets, even during the crisis period. Within-country idiosyncrasies explain about 43 percent of Russian equity market volatility and about 71 percent for Chinese equity markets. The distinct political economy of these countries, which is less aligned with advanced open economies, could be a possible explanation for the high level of within-country idiosyncrasies. These results suggest that the benefits from international portfolio diversification in these countries exist even during the crisis period.

During the global financial crisis the financial sector was the first and most affected segment of the economy. However, Table 2.6 shows that the contagion effects from the US financial sector to the other advanced economies in the sample

Table 2.6: Unconditional volatility decomposition of financial sector index returns (contribution to total volatility, in percent)

Country	Crisis Period			Non-crisis Period	
	Common Factor	Idiosyncratic Factor	Contagion from US	Common Factor	Idiosyncratic Factor
Panel A: Contagion Effect from US to Advanced Economies					
US	18.45	81.55		10.16	89.84
France	90.58	5.52	3.91	94.26	5.74
Germany	76.04	18.24	5.72	80.65	19.35
Japan	6.26	23.35	70.39	21.14	78.86
UK	79.94	18.50	1.56	81.21	18.79
Panel B: Contagion Effect from US to Emerging Economies					
US	80.89	19.11		4.33	95.67
Brazil	52.06	23.30	24.64	69.08	30.92
China	0.40	68.24	31.35	0.58	99.42
India	0.02	26.26	73.72	0.07	99.93
Russia	0.03	45.04	54.93	0.07	99.93

(except Japan) are not large, particularly when compared to the overall equity market linkages reported in Table 2.5. The US financial sector shocks explain about 4 percent of the volatility in the French financial sector, 6 percent in the German financial sector and 2 percent in the UK financial sector. The reasons for this dramatic difference between these and the overall equity market linkages seem likely to lie with the literature on the role of financial integration and business cycle synchronization. Financial sectors in the advanced economies are known to be strongly integrated (Bekaert et al., 2009). Although the theoretical literature debates whether financial integration and output cycles are positively correlated, recently Kalemli-Ozcan et al. (2013) provided empirical evidence that financially integrated markets may have less correlated output during non- crisis periods, but that during periods of financial stress output correlation will increase. And further, global banking linkages have a significant role to play in this feature. The evidence presented in Tables 5 and 6 is consistent with these findings. The transmission of contagion, which accounts for increased correlation over that normally observed in the markets, is higher for the index which includes the effects on the real economy than in just the financial sector. The financial sector here is not experiencing much increase in transmission above what would normally be expected (the contribution of the common factor has not altered substantially).

Unlike the other advanced economies, the Japanese financial sector experiences large shocks from the US financial sector despite evidence that the Japanese financial system is assumed to be resilient to external influences (IMF, 2009a; Kawai and Takagi, 2009).[8] The literature suggests that during the early phase of the GFC, the Japanese financial system was in fact robust to the global market turmoil, but the aftershocks of the Lehman Brothers collapse increased the uncertainty in the market and destabilized the Japanese financial system (IMF, 2008, 2009). Consistent with the results in this paper, the IMF (2008) attributes the increased uncertainty in the Japanese financial markets to the global repricing of risk rather than domestic concerns.

The contagion effects of the US financial sector in emerging markets are similar to those in the overall equity market. Shocks from the US financial sector explain about one quarter of Brazilian financial sector volatility and about one third of Chinese financial sector volatility. The Indian financial sector experiences more contagion effects. The US financial sector shocks explain about 74 percent of the volatility during the crisis period. This evidence that the contagion effects measured using the financial index do not differ much from those using the entire index is consistent with the arguments previously invoked about the role of financial integration during crises. These emerging markets are not strongly integrated, meaning that during the financial crisis they did not suffer from as much increase in their real economy correlation as the more integrated advanced markets following the evidence of Kalemli-Ozcan et al. (2013).

We transform the results in Table 2.5 and 2.6 into their squared basis point equivalent by multiplying these results by the variance on the returns on mar-

[8]During the earlier episodes of financial crises, particularly the Asian crisis of 1997, despite its close proximity to other Asian countries experiencing severe financial crisis (e.g. Indonesia, Korea, Thailand), the Japanese financial system experienced less or no contagion effects (Chiang et al., 2007; Chiang and Zheng, 2010).

ket index for each country. The estimated variance decompositions in squared basis points are reported in Table 2.7. This transformation of results quantifies the contagion effects in a meaningful way. For example, the US shocks explain 70 percent of the volatility of the Japanese financial sector returns and about 74 percent of the volatility of the Indian financial sector return. However, the magnitude of the effects on squared basis points in the Indian financial sector is about twice the effects on the Japanese financial sector.

In squared basis points, the US contagion contributes to the increase in the variance of the UK equity market by 3.961 squared basis points, which is the most amongst the advanced equity markets. The US contagion shocks contribute to the variance of the Japanese equity market by 0.785 square basis points. Amongst the emerging equity markets, the US contagion shocks contribute to a large increase in the variance of these markets, particularly in the Indian and Russian markets. The magnitude of contagion shocks in squared basis points is greater for the Russian equity market than for the Indian equity market, although the US contagion shocks explain a larger proportion of the Indian equity market volatility than the Russian equity market volatility, as shown in Table 2.5. The results suggest that the US contagion shocks increase the variance of the Russian equity market in greater scale than that of the Indian equity market. Similarly, the US shocks increase the volatility of the Brazilian equity market more than that of the Japanese market (2.341 versus 0.785 squared basis points), although the proportion of the contribution of US shocks in the Japanese equity market is higher than in the Brazilian equity market.

In the financial sectors, the contagion from the US financial sector accounts for about 5.5 square basis points in the total variance of the Japanese financial market. The square point basis contribution of US financial sector shocks is higher for emerging financial sectors. For example, the US shocks account for about 11.5 square basis points for the variance in the Indian financial sector returns and about 10.4 square basis points for the variance in the Russian financial sector

Table 2.7: Unconditional volatility decomposition (expressed in squared returns)

Country	Equity Market				Financial Sectors			
	Common factor	Idiosync factor	Contagion from US	Total	Common factor	Idiosync factor	Contagion from US	Total
Panel A: Advanced economies								
US	2.638	2.225	0.000	4.863	2.626	11.604	0.000	14.229
France	1.425	0.037	3.865	5.327	9.047	0.551	0.390	9.987
Germany	0.829	0.285	3.648	4.762	5.137	1.232	0.387	6.756
Japan	1.110	2.206	0.785	4.102	0.489	1.823	5.497	7.809
UK	1.663	0.457	3.960	6.080	9.187	2.126	0.179	11.493
Panel B: US and Emerging economies								
US	2.957	1.906	0.000	4.863	11.511	2.719	0.000	14.229
Brazil	5.882	2.798	2.341	11.022	6.180	2.766	2.925	11.871
China	0.040	4.264	1.721	6.026	0.029	4.917	2.259	7.205
India	0.000	1.138	6.670	7.808	0.002	3.516	9.873	13.391
Russia	0.094	5.506	7.315	12.915	0.006	8.239	10.047	18.292

returns.

2.4.3 Robustness and Sensitivity Analysis of Results

We also examined contagion from the US financial sector to the aggregate equity markets in other countries and contagion from the US equity market to the financial sector of other markets. The results are consistent, i.e. the financial markets in advanced countries (except Japan) experience very small contagion effects from the US (equity market or financial sector). In addition, we considered September 15, 2008 to May 29, 2009 as the crisis period. We also performed the sensitivity analysis for geographic time differences considering (i) data as it is, that is, without time adjustment, and (ii) using the 2-day rolling over moving average (as in Forbes and Rigobon (2002)). The central results remain the same.

2.5 Concluding Remarks

The global financial crisis has been widely characterized as beginning with the real estate bubble burst and sub-prime crisis in the US. This was followed by a sharp decline in equity market indices in the US and subsequently in other countries. The crisis was not limited to advanced economies. Many emerging economies experienced even sharper decreases in stock market indices. This paper examined the contagion effects from the US to advanced and emerging economies during the global financial crisis using a latent factor model. We found significant contagion effects from the US equity market to equity markets in both advanced and emerging economies. The contagion factors were the dominant factors explaining the volatility of these markets during the crisis period. However, we found less contagion effects from the US financial sector to the financial sector of advanced economies except Japan. Our results suggest that contagion effects are not strongly related to the level of global integration.

Our results point to several interesting areas for future research. One avenue might be identifying the explicit pathways of transmission (e.g. trade and financial linkages and interbank networks) of the crisis effects such as in Glick and Rose (1999), van Rijckeghem and Weder (2001, 2003), Rose and Spiegel (2010) and Park and Song (2001). Another interesting avenue for additional research is to study the potential causes of contagion. A broader understanding of potential channels of crisis transmission including contagion might hold greater policy significance during a time of financial turmoil.

Chapter 3

Identifying Contagion Using a Conditional Factor Model

3.1 Introduction

Financial contagion is a crisis phenomenon associated with higher market volatility and stronger comovement of markets than normal periods. Empirical approaches measuring financial contagion largely focus on quantifying this comovement of markets during highly volatile periods and rely on correlation measures such as correlation coefficients or beta coefficients (Bekaert et al., 2005; Dungey et al., 2005; Forbes and Rigobon, 2002; Hwang et al., 2013; Kasch and Caporin, 2013). A limitation of the conventional correlation measure is that it tends to be biased upwards when series experience high volatility (Forbes and Rigobon, 2002). Polson and Scott (2011) suggest that in a market model framework an illusion of excess correlation may arise if we ignore time varying volatility because cross-market correlations are conditional upon the aggregate market volatility.

A number of authors have attempted to correct for this bias while testing for contagion. For example, Forbes and Rigobon (2002) suggest adjusting for the upward bias in cross-market correlation by considering the increased volatility of the source market during the crisis period, while Corsetti et al. (2005) offer an adjustment to the correlation coefficient based on the changes in the variance ratios of common and idiosyncratic factors during the crisis period. The possible drawbacks of the Forbes and Rigobon (2002) approach are (i) it often underestimates the adjusted correlation coefficient and (ii) the true underlying relationship may experience a break or shift during the crisis period because of some policy initiatives. The Corsetti et al. (2005) approach relaxes the assumption of a constant underlying relationship between two markets but assumes that the variance within sub-sample periods remains constant - which is not necessarily true. Dungey and Renault (2013) offer a latent factor volatility model which accounts for heteroskedasticity and considers the potential source of contagion through a common factor or systematic risk.

In this chapter, we apply the Dungey and Renault (2013) model and adjusted correlation approach of Forbes and Rigobon (2002) and re-examine financial contagion in equity markets for advanced and emerging economies for the global financial crisis (GFC) of 2007-2009. Applying the approach of Dungey and Renault (2013) we more specifically test for a change in common factor loading during the crisis period. In this sense, contagion here refers to 'fundamentals based contagion' (Kaminsky and Reinhart, 1998). The results reveal that most of the sample aggregate equity markets experienced significant change in their structural relationship with the US aggregate equity market suggesting contagion through the systematic channel. However, the structural relationship between the US financial sector and the financial sectors of other economies has broken completely during the crisis period, indicating the potential for policy initiatives, such as restrictions on cross-border merger, to shield domestic financial sectors from crisis in the US financial sector. Interestingly, when we apply the adjusted correlation coefficient approach of Forbes and Rigobon (2002), we observe that the adjusted correlation coefficient between US and other sample market decreases significantly during the crisis period.

This chapter contributes to the growing body of literature on global financial crisis and contagion effects and is closely related to Chapter 2 of this dissertation. However, this chapter differs in three major aspects. First, the way we define contagion is different - this chapter focuses on fundamentals based contagion or systematic contagion whereas Chapter 2 focuses on idiosyncratic contagion. Second, this chapter uses a conditional factor volatility model whereas Chapter 2 is based on an unconditional factor model. Finally, this chapter incorporates heteroskedasticity issue in data whereas Chapter 2 assumes homoscedasticity. The results from this chapter contribute to our understanding on different aspects of financial contagion during the GFC.

The rest of the chapter is organized as follows. Section 3.2 presents the modeling framework for contagion tests including a description of the conditional factor model of Dungey and Renault (2013). Section 3.3 describes the sample, data and empirical implementation of the conditional factor model. Results and discussion are presented in Section 3.4 and Section 3.5 concludes the chapter.

3.2 The Modeling Framework

3.2.1 Motivation

There are several issues with identifying financial contagion empirically, particularly in the correlation based approach. The most difficult of these is related to the issue of time-varying volatility.

Suppose that one has specified the relationship between two markets (x and y) in a bivariate regression framework as follows:

$$y_t = \alpha + \beta x_t + \epsilon_t \tag{3.1}$$

where $E[\epsilon_t] = 0$, $E[\epsilon_t^2] = c < \infty$(where c is a constant), and $E[x_t\epsilon_t] = 0$. Consider a normal period (l) which is likely to be less volatile, a crisis period (h) which is likely to be more volatile, and assume that the underlying relation between two markets remains constant in both normal and crisis periods, that is, $\beta^h = \beta^l$ which implies:

$$\beta^h = \frac{Cov[x,y]^h}{Var[x]^h} = \frac{Cov[x,y]^l}{Var[x]^l} = \beta^l. \tag{3.2}$$

By construction, $Var[x]^h > Var[x]^l$, which implies that $Cov[x,y]^h > Cov[x,y]^l$. The second order moment condition for Eq. (3.1) can be expressed as

$$Var[y] = \beta^2 Var[x] + Var[\epsilon]. \tag{3.3}$$

Since the variance of the residual is positive, the increase in the variance of y across periods is less than proportional to the increase in the variance of x (see Forbes and Rigobon (2002) for further details and proof). In other words,

$$\left(\frac{Var[x]}{Var[y]}\right)^h > \left(\frac{Var[x]}{Var[y]}\right)^l. \tag{3.4}$$

Now, consider the standard definition of the correlation coefficient (ρ):

$$\rho_{xy} = \frac{Cov[x,y]}{\sqrt{Var[x]Var[y]}} = \beta\sqrt{\frac{Var[x]}{Var[y]}}. \tag{3.5}$$

When we substitute Eq. (3.2) into Eq. (3.5) and consider the relationship expressed in Eq. (3.4), we obtain

$$\rho_{xy}^h > \rho_{xy}^l. \tag{3.6}$$

Therefore, Eq. (3.6) implies that the estimated correlation between x and y increases when the variance in x increases. Therefore, ignoring the effect of time-varying volatility can lead to spurious findings of excess correlation.

The Forbes and Rigobon (2002) approach tests for a significant difference between the unconditional correlation coefficient (after adjusting for increased variance) during a crisis period and the correlation coefficient during a non-crisis period. The crisis period unconditional correlation coefficient is given as:

$$\widetilde{\rho}_{xy}^{h} = \frac{\rho_{xy}^{h}}{\sqrt{1+\delta\left[1-\left(\rho_{xy}^{h}\right)^{2}\right]}}, \tag{3.7}$$

where $\delta = \left[Var[x]^{h} - Var[x]^{l}\right]/Var[x]^{l}$, the proportional change in variance during the crisis period. Therefore, the null hypothesis is:

$$H_0 : \widetilde{\rho}_{xy}^{h} = \rho_{xy}^{l} \tag{3.8}$$

against the alternative hypothesis of:

$$H_1 : \widetilde{\rho}_{xy}^{h} > \rho_{xy}^{l} \tag{3.9}$$

A rejection of the H_0 is consistent with the presence of contagion.[1] Considering the finite sample properties of financial data and the fact that the correlation coefficient is bounded between +1 to -1, Forbes and Rigobon (2002) suggest using Fisher's transformation where the resulting t-stat is given by:

$$\frac{\frac{1}{2}ln\left(\frac{1+\widetilde{\rho}_{xy}^{h}}{1-\widetilde{\rho}_{xy}^{h}}\right) - \frac{1}{2}ln\left(\frac{1+\rho_{xy}^{l}}{1-\rho_{xy}^{l}}\right)}{\sqrt{\frac{1}{T_1-3}+\frac{1}{T_2-3}}} \tag{3.12}$$

where T_1 and T_2 refer to pre-crisis and crisis periods respectively.

A limitation to the correlation coefficient approach of Forbes and Rigobon (2002) even with this correction, is that it assumes constant variance within subsample periods which is less likely in the case of financial return series.

Dungey et al. (2005) show that the variance adjustment in the correlation

[1] In their actual empirical setting, Forbes and Rigobon (2002) test the following hypotheses:

$$H_0 : \rho_{xy} > \widetilde{\rho}_{xy}^{h} \tag{3.10}$$

$$H_1 : \rho_{xy} \leq \widetilde{\rho}_{xy}^{h} \tag{3.11}$$

where ρ_{xy} is the correlation coefficient based on full sample period indicating that any t-test value greater than t-test critical value at 5 percent indicates evidence of contagion while any t-test value less or equals to critical value indicates no contagion.

coefficient can be equivalently implemented in a regression framework such as Eq.(3.1) for the crisis period as

$$y_t^h = \alpha + \tilde{\beta}^h \widetilde{x}_t^h + \epsilon_t^h \tag{3.13}$$

where

$$\widetilde{x}_t^h = x_t^h / \sqrt{(1+\delta\widetilde{\rho}_{xy}^h)/(1+\delta)}; t = (1, ..., T_2) \in T_2. \tag{3.14}$$

The test of contagion equivalent to Eq. (3.8) is:

$$H_0 : \tilde{\beta}^h = \beta^l. \tag{3.15}$$

Dungey and Renault (2013) argue that Forbes and Rigobon (2002) approach of adjustment in correlation coefficient may overestimate the spurious component of correlation increase so that their proposed test tends towards an erroneous conclusion of "no contagion". This is the most likely case when the volatility of the recipient market, y, increases more than the volatility of the source market, x, during the crisis period.[2] Considering this heteroskedasticity issue and potential time varying structural relationship between crisis originating market and recipient markets, Dungey and Renault (2013) propose a conditional factor model.

3.2.2 The Conditional Factor Model[3]

Consider a simple latent factor model of asset pricing where the return on risky assets $(r_1, r_2, ..., r_n)$ is a function of a common factor and can be represented as:

$$r_{i,t+1} = \lambda_i F_{t+1} + \varepsilon_{i,t+1} \; i = 1, ..., n \tag{3.16}$$

[2]To overcome the heteroskedasticity issue, some recent studies compute the conditional correlation from dynamic conditional correlation (DCC) GARCH approach (Engle, 2002) and test for a significant increase in conditional correlation during the crisis period (Chiang et al., 2007; Wang and Nguyen Thi, 2012), under the null hypothesis of no contagion, $\rho_{y(DCC)} = \rho_{x(DCC)}$. The DCC approach overcomes the endogeneity issue in the Forbes and Rigobon (2002) approach by computing the conditional correlation coefficient from GARCH model residuals.

[3]This section is largely drawn from Dungey and Renault (2013).

where $r_{i,t+1}$, F_{t+1} and $\varepsilon_{i,t+1}$ are the excess return of risky asset i, the common factor, and the model residual respectively, and all of which have a zero conditional expectation at time t. λ_i is the factor loading of asset i. Dungey and Renault (2013) show multiple factors are possible but in practice most financial data confirms the existence of one common factor.

Eq.(3.16) can be identified through the structure of conditional moment conditions given by

$$Cov_t[F_{t+1}, \varepsilon_{i,t+1}] = 0, \;\; i = 1, ..., n \tag{3.17}$$

$$Cov_t[\varepsilon_{i,t+1}, \varepsilon_{j,t+1}] = \omega_{i,j}, \;\; i, j = 1, ..., n. \tag{3.18}$$

Eq.(3.17) and (3.18) suggest that the conditional variance of the common factor is the only source of time variation of conditional variances and covariances of asset returns (Dungey and Renault, 2013).

To characterize financial contagion within such a factor model, consider the asset return on the crisis originating country, r_n, as a mimicking factor, then

$$r_{i,t+1} = b_i r_{n,t+1} + \varepsilon_{i,t+1}; \; i = 1, ..., n-1 \tag{3.19}$$

where a structural break in the coefficient b_i for the crisis period can be considered as evidence of contagion. As covered in Section 3.2.1, ignoring the potential changes in variance of r_n over time may result in spurious changes in b_i during the crisis period. To overcome this issue, Dungey and Renault (2013) suggest that expressing the data generating process of the mimicking asset return as:

$$r_{n,t+1} = F_{t+1} + \varepsilon_{n,t+1} \tag{3.20}$$

with variance

$$Var(r_{n,t+1}) = Var(F_{t+1}) + Var(\varepsilon_{n,t+1}). \tag{3.21}$$

and

$$Var(F_{t+1}) = \alpha Var(r_{n,t+1}). \tag{3.22}$$

The choice of normalization constant α is limited by the constraint to ensure positivity:

$$\alpha \geq 1 - \frac{MinVar_t(r_{n,t+1})}{Var(r_{n,t+1})} = \bar{\alpha} \tag{3.23}$$

where $MinVar_t(r_{n,t+1})$ is the minimum of $Var_t(r_{n,t+1})$. Since the $E[Var_t(r_{n,t+1})]= Var(r_{n,t+1})$, we have $1 > \bar{\alpha} \geq 0$, indicating that the return $(r_{n,t+1})$ is conditionally heteroskedastic (Dungey and Renault, 2013). Assigning $\bar{\alpha}Var(r_{n,t+1})$ amount of variance to the factor captures the time varying part of the conditional variance (Dungey and Renault, 2013). The normalization parameter α can be derived from a univariate GARCH process, where the implied conditional variance path provides $MinVar_t(r_{n,t+1})$, and the unconditional variance from the sample provides $Var(r_{n,t+1})$. Eq. (3.22), which hence implies that if the unconditional variance of the mimicking asset, r_n, increases, the variance of common factor should increase in the same ratio to keep the underlying relation between them unchanged.

Dungey and Renault (2013) suggest the generalized method of moments (GMM) to estimate the parameters of the model, where the moment condition restrictions are:

$$E_t[r_{j,t+1}(r_{i,t+1} - b_i r_{n,t+1})] = c_{ij,\, j=1,...,n; i=1,...,n-1} \tag{3.24}$$

and

$$E[r_{i,t}r_{n,t} - b_i \alpha r_{n,t-1}^2 - w_{i,n}] = 0. \tag{3.25}$$

where (b_i, c_{ij}, w_{in}) are the unknown parameters. Eq. (3.24) is the conditional moment restriction whereas Eq. (3.25) is the unconditional moment restriction.

In a GMM framework, these moment restrictions are implemented via an $(n+1)$ vector of instruments $z_t = [1, r_{1,t}, r_{2,t}, ..., r_{n,t}]'$. The estimation of Eq. (3.24) for a vector of returns r_i and instruments can be written as:

$$\underbrace{r_{i,t+1}[r_{t+1}\otimes z_t]}_{Y_{i,t+1}} = \underbrace{b_i\left[r_{n,t+1}\otimes(r_{t+1}\otimes z_t)\right]+c_i\left[I_n\otimes z_t\right]}_{X_{t+1}\theta_i} + u_{i,t+1} \tag{3.26}$$

where r_{t+1} is a set of n assets which yields $n(n+1)$ column matrix for $[r_{t+1}\otimes z_t]$, the notation $\otimes$ denotes Kronecker product, I_n is the identity matrix of dimension n, u_i is residual and $\theta_i = \{b_i, c_i\}$ contains unknown parameters of interest. The unconditional moment restriction

$$E[u_{i,t+1}] = 0 \tag{3.27}$$

helps to identify these unknown parameters in Eq. (3.26). Starting values for parameters are obtained by running ordinary least square (OLS) in the univariate regression by averaging Eq. (3.26) over time, that is:

$$\theta_{i,T(OLS)} = \left[\overline{X}_T\overline{X}_T^{'}\right]^{-1}\overline{X}_T^{'}\overline{Y}_{i,T} \tag{3.28}$$

where $\overline{Y}$ and $\overline{X}$ refer to average over time, t=1,...,T.

Eq. (3.26) does not take into account the arguments provided in Eq. (3.20)-(3.22). As shown in Dungey and Renault (2013), the extension of Eq. (3.26) considering Eq. (3.22) can be written as:

$$\begin{bmatrix} r_{i,t+1}[r_{t+1}\otimes z_t] \\ r_{i,t+1}r_{n,t+1} \\ r_{n,t+1}\odot r_{n,t+1} \end{bmatrix} = \begin{bmatrix} b_i\left[r_{n,t+1}\otimes(r_{t+1}\otimes z_t)\right]+c_i\left[I_n\otimes z_t\right] \\ b_i\left[e\otimes(\alpha\odot r_{n,t+1}\odot r_{n,t+1})\right]+w_i \\ (1-\alpha)^{-1}w_n \end{bmatrix} + \begin{bmatrix} \tilde{u}_{iz,t+1} \\ \tilde{u}_{in,t+1} \\ \tilde{u}_{nn,t+1} \end{bmatrix} \tag{3.29}$$

or

$$\widetilde{Y}_{i,t+1} = \widetilde{X}_{t+1}\widetilde{\theta}_i + \widetilde{u}_{i,t+1} \tag{3.30}$$

where $\odot$ refers to component-wise product, or Hadamard product, e is a vector of ones and $\theta_i = [b_i, c_i, w_i, w_n]$. The first row in Eq.(3.29) is same as in Eq.(3.26). The second and third rows in Eq. (3.29) add the linear expression of covariance and variance. Now, the parameters of interest can be estimated with the moment restrictions specified in Eq. (3.24), (3.25) and (3.27).

3.3 Sample, Data and Empirical Implementation

3.3.1 Sample and Data

We consider the daily returns for the aggregate equity market and financial sector of the 9 largest economies in terms of gross domestic product (5 advanced countries: France, Germany, Japan, UK, and the US; and 4 emerging economies: Brazil, China, India and Russia) considering the the US as a crisis origin country. The sample period is from August 2, 2004 to May 30, 2009 with corresponding crisis period from July 19, 2007 to May 30, 2009, as identified in Chapter Two. We extract the daily data for the aggregate equity market index and financial sector index from Thompson Reuters Datastream.

3.3.2 Empirical Implementation

As suggested in Dungey and Renault (2013), we estimate the normalization parameter α from a univariate GARCH(1,1) process applied to the US aggregate equity index returns data, as it is a mimicking factor in our model. The estimated value of α is 0.87. We also performed sensitivity analysis for different values of $\alpha[= 0.6, 0.7, 0.9]$. In our sample, we have a total of 9 assets ($n = 9$) representing 9 equity indices. Returns on the US equity market index provide our mimicking factor, r_n, and is consistent with literature that the US index can proxy for the common factor or global factor (Bekaert et al., 2005, 2014).

We choose a constant and squared lagged returns as instruments. As we have 9 assets we choose 10 ($= n+1$) instruments $[z_t = (1, r_{1,t}^2, ..., r_{10,t}^2)]$. As we perform asset-by-asset estimation, for a pre-crisis period, T_1 and crisis period, T_2 (where $T_1 + T_2 = T$), for each $Y_{i,t+1}$ we have 90 ($= n(n+1)$) columns. Over each estimation window, we compute $Y_{i,}$ for each day (t) and average it over the estimation window. Doing this provides 90 mean observations for Y and 1 mean observation for (r_i, r_n), the second row of Eq.(3.29).[4] The estimation of $\widetilde{X}_{t+1}$ follows a similar process. The GMM estimates for $\theta_{i,T}$ can be estimated as:

$$\widetilde{\theta}_{i,T,GMM} = \left[\overline{\overline{\widetilde{X}}}_T \left(\widetilde{\Sigma}_{i,T} \right)^{-1} \overline{\overline{\widetilde{X}}}'_T \right]^{-1} \overline{\overline{\widetilde{X}}}'_T \left(\widetilde{\Sigma}_{i,T} \right)^{-1} \overline{\overline{\widetilde{Y}}}_{i,T} \tag{3.31}$$

where $\left(\widetilde{\Sigma}_{i,T} \right)$ is the OLS consistent estimator of the covariance matrix:

$$\widetilde{\Sigma}_{i,T} = \frac{1}{T} \sum_{t=1}^{T} (\widetilde{u}_{i(\theta,OLS)})(\widetilde{u}_{i(\theta,OLS)})' \tag{3.32}$$

and works as a weighting matrix in Eq.(3.31). As suggested in Dungey and Renault (2013), we choose 5-day rolling moving averages for r_n to correct for serial correlation.

Considering contagion as a crisis phenomenon, we split the sample period into a pre-crisis period (T_1) and crisis period (T_2), and implement the factor model. The test of contagion for asset $i = 1, ..., n-1$ therefore refers to significant differences between $\widetilde{\theta}_{i,T_1,GMM}$ and $\widetilde{\theta}_{i,T_2,GMM}$, in particular $b_{i,T1}$ and $b_{i,T2}$, where the standalone statistical significance of $b_{i,T1}$ and $b_{i,T2}$ indicates an underlying structural relationship between asset i and the mimicking factor.

We also implement the Forbes and Rigobon (2002) approach in Eq.(3.8) and (3.15), and test for contagion in our sample markets.

[4]The third row of $\widetilde{Y}_{i,t+1}$will have a constant term in right hand side so does not enter into the estimation process.

3.4 Results

Table 1 provides the results for tests of contagion in our sample. Panel A of Table 3.1 provides the pairwise correlation coefficient between US equity market returns and the equity market returns for other sample countries. Amongst the sample markets, a distinct pattern of comovement with the US equity markets is clearly evident. Most of the advanced equity markets (except for Japan) have a high degree of correlation with the US equity market suggesting a high level of equity market integration in advanced countries (Bekaert and Harvey, 1995; Bekaert et al., 2005). The emerging equity markets (except for Brazil), however have a comparatively low level of correlation with the US equity market indicating low level of market integration. The results for Brazil however suggest a high level of regional integration of the Brazilian equity market with the US equity market. The Chinese equity market has the lowest level of market comovement with the US equity market in the sample.

The unconditional correlation coefficient for all the markets in sample (except China) increased significantly during the crisis period as shown in the row labeled 't-test naive' in Panel A of Table 3.1. However, when adjusted for heteroskedasticity as suggested in Forbes and Rigobon (2002) shown in the row labeled 't-test corrected', the crisis period coefficient decreases significantly for all the markets (except China). The correlation coefficients for China are insignificantly different using both measures. If we consider the one-tail test of significant increase in correlation during the crisis period as evidence for contagion (as in Forbes and Rigobon (2002)), the null of no contagion could not be rejected.[5]

Results from the regression based approach of Dungey et al. (2005) are reported in Panel B of Table 3.1. The results are similar to results reported in Panel

[5]However, considering decreased correlation against evidence of contagion may be misleading. The literature suggests that a crisis may have spillover effects in other countries, therefore, policy makers of other countries may impose restrictions to reduce the crisis effect originated elsewhere. In such cases magnitude of comovement of these two markets may reduce. Similarly, when policy makers impose restrictions to reduce crisis effects it may systematically distort the existing comovement (linkages) of markets which may lead to decrease in correlation.

Table 3.1: Test for contagion in equity markets

Equity Market	country	Brazil	China	France	Germany	India	Japan	Russia	UK
Panel A: Correlation coefficients									
	Pre-crisis	0.65	0.07	0.64	0.69	0.27	0.28	0.31	0.62
	Naive	0.75	0.12	0.75	0.77	0.40	0.41	0.48	0.74
	Corrected	0.34	0.04	0.34	0.37	0.14	0.14	0.17	0.34
t-test naive	t-Stat	3.36	0.82	3.63	3.20	2.63	2.64	3.42	3.89
	p-Value	0.02	0.24	0.02	0.03	0.04	0.04	0.02	0.02
t-test corrected	t-Stat	-7.32	-0.60	-7.04	-7.99	-2.32	-2.40	-2.58	-6.62
	p-Value	0.00	0.30	0.00	0.00	0.05	0.05	0.04	0.00
Panel B: Regression coefficients									
Pre-crisis period	Estimate	1.17	0.19	0.74	0.78	0.55	0.41	0.81	0.64
	S.E.	0.05	0.08	0.03	0.03	0.07	0.05	0.09	0.03
	t-Stat	24.34	2.29	23.87	26.94	7.92	8.26	9.42	22.68
Crisis period (naive)	Estimate	0.86^a	0.15^a	0.69^a	0.68^a	0.51^a	0.43	0.81	0.70^a
	S.E.	0.03	0.05	0.03	0.03	0.05	0.04	0.07	0.03
	t-Stat	25.26	2.78	25.20	27.16	9.78	10.01	12.15	24.67
Crisis period (corrected)	Estimate	0.32^a	0.06^a	0.26^a	0.26^a	0.19^a	0.16^a	0.31^a	0.26^a
	S.E.	0.01	0.02	0.01	0.01	0.02	0.02	0.03	0.01
	t-Stat	25.26	2.78	25.20	27.16	9.78	10.01	12.15	24.67

(continued on next page)

Table 3.1 *continued*: Test for contagion in equity markets

Equity markets		Brazil	China	France	Germany	India	Japan	Russia	UK
Panel C: J-test for identification									
Pre-crisis	$J-Stat$	0.21	0.52	0.19	0.18	0.30	0.27	0.28	0.22
	p-Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Crisis	$J-Stat$	0.73	0.48	0.59	1.05	0.80	0.72	0.88	0.64
	p-Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel D: Tests for structural stability									
Ghysels-Hall	$Chi-sq$	106.39	84.90	110.90	108.47	106.60	88.99	109.65	121.95
	p-Value	0.11	0.63	0.07	0.09	0.11	0.51	0.08	0.01
Break in factor loadings	$Chi-sq$	158.50	72.79	195.86	102.28	109.34	111.27	75.09	153.25
	p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Break in number of factors	$J-Stat$	0.73	0.48	0.59	1.05	0.80	0.72	0.88	0.64
	p-Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel E: Factor loadings									
Pre-crisis	Estimate	3.00	0.90	2.03	1.92	4.36	2.73	4.99	1.84
	S.E.	0.05	0.25	0.02	0.03	0.54	0.09	0.82	0.02
	t-Stat	58.33	3.68	96.68	69.54	8.15	29.87	6.08	90.32
Crisis	Estimate	1.05	1.16	0.91	1.15	1.57	1.29	1.31	0.90
	S.E.	0.49	0.35	0.15	0.39	0.75	0.56	1.66	0.33
	t-Stat	2.15	3.36	6.31	2.94	2.11	2.30	0.79	2.76
t-test for change	t-Stat	-88.89	14.56	-170.53	-43.35	-72.25	-56.83	-45.74	-64.26
	p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: a indicates significantly smaller than pre-crisis estimate based on t-test.

A. However, the unconditional regression coefficients for the crisis period are generally smaller than the coefficients for the crisis period and the heteroskedasticity corrected regression coefficients for crisis period are even smaller. The significant change in the regression coefficient for the crisis period suggests that the underlying relationship between the two markets has changed during the crisis period.

The results from the conditional factor model of Dungey and Renault (2013) are reported in Panel C, D and E of Table 3.1. Panel C reports the J-test results under the null of a single factor specification across pre-crisis and crisis periods. The results suggest that a single factor model captures the dynamics of the data generating process for each period in our sample. We test for structural stability using a Hall (2005) test against the null of no break in the factor loadings in Panel D. The null hypothesis is rejected for all of our sample markets, supporting our specification of a single factor across both periods, but allowing for a break in factor loadings in the pre-crisis and crisis periods. These results are further supported by Ghysels and Hall (1990) test of structural change where the joint null of no changes in either the model specification or the parameter loadings between the two periods is rejected in all the countries except China and Japan.[6]

The factor loadings for all the sample equity markets are significant for both pre-crisis and crisis periods with the exception of the Russian equity market where the factor loading for the crisis period is not statistically significant at conventional levels, as shown in Panel E of Table 3.1. These statistically significant results suggest that the mimicking asset (aggregate US equity market returns) can explain the returns of other sample markets - both advanced and emerging in both pre-crisis and crisis periods. When we perform a test for significant difference between pre-crisis and crisis periods loadings, the null of no difference is rejected for all the sample markets. As we are using the US equity market return as a mimicking factor, the significant difference in common factor loadings

[6] The results for Brazil and India are marginally significant (at 11 percent).

provides evidence for contagion from the US to other markets during the GFC. More specifically this result suggests transmission of crisis through a common factor. The established relationship between the US equity market and equity markets of other sample countries has changed but not broken completely during the crisis period. Consistent with these results, Fratzscher (2012) shows that the common shock effects through capital flows (or portfolio re-balancing) affected both emerging and advanced economies during the GFC. Zhang et al. (2013) also provide evidence of change in comovement between the US equity market and equity markets of emerging economies during the GFC.

Chapter 2 provides less evidence of contagion in the financial sector than in aggregate equity market. We apply the conditional factor model to the financial sector of sample countries and re-examine the contagion effects. The results are provided in Panel A through E of Table 3.2. Although the results using correlation coefficients and the regression approach are similar to results for aggregate equity markets, the results from the single factor model are interesting. For the pre-crisis period, factor loadings are positive and statistically significant. However, during the crisis period, the factor loadings are not statistically significant (except for Germany) indicating that the US financial sector returns as the mimicking portfolio is not able to explain the returns on other sample countries' financial sectors. There are a number of possible reasons behind not finding a significant coefficient for crisis period. Most of the policy initiatives and market interventions focused on financial sectors, particularly designed to insulate the domestic economy from effects of the crisis in the US financial sector through initiatives such as restrictions on cross-border mergers and acquisitions of financial institutions, and liquidity and capital support to local banks by central banks. Such actions help to break the existing linkages of relationship between financial sectors across the countries. For example, Ait-Sahalia et al. (2012) find that policy interventions, in particular in financial sector reduced the interbank credit and liquidity risks in advanced economies. Klyuev et al. (2009) state that policy

Table 3.2: Test for contagion in financial sector indices

Equity Market	country	Brazil	China	France	Germany	India	Japan	Russia	UK
Panel A: Correlation coefficients									
	Pre-crisis	0.50	0.13	0.57	0.60	0.20	0.19	0.16	0.53
	Naive	0.62	0.09	0.63	0.68	0.35	0.33	0.40	0.65
	Corrected	0.16	0.02	0.17	0.19	0.08	0.08	0.09	0.17
t-test naive	t-Stat	3.07	-0.76	1.78	2.45	2.99	2.49	4.64	3.22
	p-Value	0.03	0.25	0.09	0.05	0.03	0.04	0.01	0.02
t-test corrected	t-Stat	-6.68	-1.98	-8.23	-8.74	-2.09	-2.16	-1.18	-7.18
	p-Value	0.00	0.07	0.00	0.00	0.06	0.06	0.16	0.00
Panel B: Regression coefficients									
Pre-crisis period	Estimate	0.99	0.34	0.73	0.68	0.47	0.37	0.51	0.57
	S.E.	0.06	0.09	0.04	0.03	0.08	0.06	0.10	0.03
	t-Stat	16.35	3.98	19.77	21.67	5.79	5.8	4.96	18.01
Crisis period (naive)	Estimate	0.47^a	0.07^a	0.52^a	0.44^a	0.36^a	0.28^a	0.49	0.56
	S.E.	0.03	0.03	0.03	0.02	0.04	0.04	0.05	0.03
	t-Stat	17.58	2.05	18.15	20.89	8.46	7.73	9.81	19.02
Crisis period (corrected)	Estimate	0.11^a	0.02^a	0.12^a	0.10^a	0.08^a	0.07^a	0.11^a	0.13^a
	S.E.	0.01	0.01	0.01	0.00	0.01	0.01	0.01	0.01
	t-Stat	17.58	2.05	18.15	20.89	8.46	7.73	9.81	19.02

(continued on next page)

Table 3.2 *continued*: Test for contagion in financial sector indices

Equity markets		Brazil	China	France	Germany	India	Japan	Russia	UK
Panel C: J-test for identification									
Pre-crisis	J-Stat	0.23	0.46	0.21	0.19	0.35	0.35	0.43	0.22
	p-Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Crisis	J-Stat	0.79	0.71	0.64	0.87	0.65	0.81	0.82	0.6
	p-Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel D: Tests for structural stability									
Ghysels-Hall	Chi-sq	119.28	112.23	117.31	111.19	111.62	98.09	123.49	127.19
	p-Value	0.02	0.06	0.03	0.06	0.06	0.26	0.01	0.01
Break in factor loadings	Chi-sq	148.48	80.89	139.76	119.73	118.36	110.03	50.17	150.6
	p-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Break in number of factors	J-Stat	0.79	0.71	0.64	0.87	0.65	0.81	0.82	0.6
	p-Value	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Panel E: Factor loadings									
Pre-crisis	Estimate	2.35	0.66	1.63	1.49	2.99	1.63	2.97	1.4
	S.E.	0.19	0.46	0.06	0.05	0.42	0.15	1.98	0.04
	t-Stat	12.31	1.43	26.1	30.22	7.05	10.62	1.5	38.59
Crisis	Estimate	0.62	0.75	0.91	0.87	1.18	1.17	1.15	0.99
	S.E.	0.54	0.83	0.6	0.42	1.13	0.99	2.06	0.62
	t-Stat	1.17	0.91	1.52	2.06	1.05	1.19	0.56	1.59
t-test for change	t-Stat	-68.85	2.27	-26.47	-32.44	-33.89	-10.06	-15.62	-14.62
	p-Value	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00

Note: a indicates significantly smaller than pre-crisis estimate based on t-test.

initiatives contributed to reduce the risk of financial system. In such case, it is most likely to take effect through common factor.

In summary, the results from conditional factor model in this Chapter are qualitatively similar to the results from unconditional factor model in Chapter 2, and provide the evidence of contagion during the GFC. In Chapter 4, we move to a more elaborate description of the potential means by which crises are transmitted and constitute contagion.

3.5 Concluding Remarks

This chapter re-examines the financial contagion in the equity markets of advanced and BRIC economies during the global financial crisis of 2007-2009 by using the conditional factor model of Dungey and Renault (2013) and the adjusted correlation approach of Forbes and Rigobon (2002). The results from the conditional factor model suggest that there exist structural relationships between the US aggregate equity market and aggregate equity market of other advanced and emerging markets; these relationships experienced a structural shift during the global financial crisis suggesting potential contagion effects via a common factor. However, the results from the financial sectors considered alone suggest that the structural relationships between the US financial sector and financial sector of other sample countries which exist during the pre-crisis period have broken completely during the crisis period. We attribute this to the impact of domestic financial sector policy initiatives to reduce the systematic crisis effect in the financial sector which originated in the US financial sector.

Chapter 4

Contagion and Banking Crises: International Evidence for 2007-2009

4.1 Introduction

Banking crises are costly, and a great deal of prudential effort is undertaken to avoid them. Bordo et al. (2001) estimate losses of around 6% of GDP associated with a banking crises in the last quarter of the 20th century, and in the most recent period Laeven and Valencia (2013) document losses of about 30% of GDP. Maintaining sound macroeconomic fundamentals, a clear legal framework and strong prudential oversight are preventative measures within the remit of domestic authorities. However, banking crises transmitted from other jurisdictions present a considerable risk to the domestic economy (Kalemli-Ozcan et al., 2013), particularly as banking crises are often observed to precede even more costly currency and debt crises (Laeven and Valencia, 2013; Reinhart and Rogoff, 2009).

This chapter empirically examines the evidence for the unexpected international transmission of banking crises via stressful conditions in financial markets.

These transmissions are beyond those which would occur by the known spillovers between banking sectors in different jurisdictions due to trading or portfolio links, and instead consist of contagion effects (Bae et al., 2003; Bekaert et al., 2005; Corsetti et al., 2005; Dungey et al., 2005; Forbes and Rigobon, 2002; Iwatsubo and Inagaki, 2007; van Rijckeghem and Weder, 2003). We find significant evidence not only for the existence of contagion, but also for its role in promoting banking crises in regions geographically removed from the crisis source. Thus, we contribute to the growing body of literature examining the role of banks in the transmission of financial crisis of 2007-2009, most of whom find evidence of international transmission via the banking sector (Allen et al., 2014; Brealey et al., 2012; Kalemli-Ozcan et al., 2013; Popov and Udell, 2012).

The model encapsulates several potential channels of contagion and testable hypotheses in a single framework. Specifically, it captures potential structural changes in global systematic risk exposure (systematic contagion), additional US idiosyncratic shocks (idiosyncratic contagion), a structural shift (shift contagion) and additional US volatility spillovers (volatility contagion). The last one captures the argument that financial markets exhibit explosive volatility during crises that may spillover to other markets (Edwards, 1998; Engle et al., 1990; Hamao et al., 1990). Using a standard factor model representation of an international CAPM framework, the model allows for spillover effects outside crisis periods (Kim, 2001; Laxton and Prasad, 2000), volatility spillovers, heteroskedasticity and skewness in the financial data with a nested EGARCH specification. The framework is most closely related to the models of Baur (2012), Bekaert et al. (2005), and Dungey et al. (2005).[1] As the crisis is widely accepted to have origi-

[1] Although our factor model framework is similar to that of Bekaert et al. (2014), it differs in a number of directions. First, we define contagion as structural shifts (changes in both intercept and slope) in factor model specification whereas they define contagion as structural shift in intercept only (crisis dummy). Second, we focus on assessing contagion across the banking sectors of 50 countries whereas they examine 415 country-sector equity portfolios across 55 countries but doesn't provide contagion results and analysis at sector level for each country. Third, our framework captures the volatility spillovers and volatility contagion whereas their framework does not. Finally, we use maximum likelihood estimator where they use pooled ordinary least square estimator.

nated in the US we consider contagion effects from the US to 49 country banking sector indices - covering both non-crisis and crisis conditions from 2001 to 2009.

There are two major results. First, we categorize the evidence for contagion between the 50 banking sectors. The banking sectors in most economies experienced contagion from the US in some form – that is systematic, idiosyncratic, shift or volatility – but not necessarily all forms. About 60 percent of our sample banking market experienced a break in global systematic risk exposure and about 60 percent of banking markets in our sample experienced idiosyncratic contagion originating from the US banking market. While most of the banking markets have volatility spillovers from the US banking market in non-crisis periods, only about 40 percent of sample banking markets experienced volatility contagion during the crisis period. Finally, shift contagion is always accompanied by other forms of contagion.

The second contribution links evidence on contagion to the occurrence of banking crises. Linking our results for contagion with the systemic banking crisis data in Leaven and Valencia (2012) reveals that crisis shocks transmitted from a foreign jurisdiction via idiosyncratic contagion increase the likelihood of a systemic crisis in the domestic banking system by almost 27 percent, whereas increased global systematic risk exposure via systematic contagion does not necessarily destabilize the domestic banking system. The existing literature argues that the probability of systemic banking crises is reduced by stronger regulatory capital (Acharya et al., 2010; Berger and Bouwman, 2013; Cole, 2012; Miles et al., 2013), the size of the banking sector and higher market concentration (Allen and Gale, 2000; Beck et al., 2006; Bretschger et al., 2012; Mirzaei et al., 2013), and reduced activity in the shadow banking sector (De Jonghe, 2010; Lepetit et al., 2008). We find that stronger regulatory capital and retail banking activities lead to reduced probability of banking crisis even in the presence of contagion effects, but that while the impact of higher market concentration is positive it is insignificant. The evidence suggests a larger economic impact of stronger regulatory capital, which reduces the probability of crisis by 11 percent, than for proportion of non-interest income in total income, which only increases the probability of crisis by less than 1 percent. Likewise, domestic conditions can help ameliorate the probability of crises, increased banking assets as a proportion of GDP lower the the probability of crisis, but the economic impact is very small, at 0.1 percent. An increase in the external debt to GDP ratio also increases the probability of crisis, by 1 percent, consistent with the hypothesis that a feedback loop exists between sovereign debt and banking crises, (Acharya et al., 2014; Adler, 2012).

Our results argue that systematic contagion effects are being adequately tackled with current policy responses – they are not significantly affecting the probability of a domestic banking crisis emerging as a result of a crisis elsewhere. However, there is scope for further reduction in banking crises promoted by international linkages via idiosyncratic contagion. Idiosyncratic contagion occurs in response to unanticipated country-specific banking sector shocks. It represents the transmission of these shocks other than via usual linkages such as portfolios or trading links which are present during non-crisis periods. Potentially there is gain for regulators and policy makers to consider how to creatively respond to calm these transmissions and extra vulnerability generated in one economy, but unexpectedly transmitting to another.

The rest of the chapter proceeds as follows. In Section 4.2, we propose a model to test for several forms of contagion and describes the sample and data. Section 4.3 provides the results for contagion. In Section 4.4 we examine the cross-section of systemic banking crisis and Section 4.5 concludes the chapter.

4.2 Modeling Financial Contagion

4.2.1 The Empirical Framework

In modern banking systems, banking institutions are often globally integrated through both on-balance sheet and off-balance sheet linkages. These global linkages make the banking sector potentially more exposed to global systematic risk than other sectors. The financial sector is known to be highly globally integrated at sectoral level (Bekaert et al., 2009). We postulate that in a globally integrated banking system the exposure of banks in a given country to global systematic risk depends on the extent of global integration of the banking system.[2]

Let $r_{i,t}$ represents the return for banking sector of country i at time t. A standard international market model representation of asset returns takes the following form:

$$r_{i,t} = a_{0,i} + a_{1,i} f_t^{global} + e_{i,t}, \tag{4.1}$$

where f^{global} refers to global factor or common shock and can be proxied by the return on the aggregate global banking sector index and $a_{1,i}$ measures the global systematic risk exposure of the banking sector of country i .

Crises may be associated with structural changes in the global systematic risk exposure of banking markets through a number of possible channels. For example, the interbank market may not function properly during the crisis period, the existing network of relationships across the market participants may break down, or the failure of a few financial institutions may have systemic impact on other banks. The potential increased exposure of banks to global systematic risk during a crisis period is denoted as systematic contagion, and is analogous to a common shocks effect or fundamentals based contagion (Baur, 2012; Bekaert et al., 2005, 2014) as revealed in Eq. (4.2) below:

[2]See Kalemli-Ozcan et al. (2013) for a recent theoretical contribution.

$$r_{i,t} = a_{0,i} + a_{1,i} f_t^{global} + a_{2,i} f_t^{global} I_t + \varepsilon_{i,t}, \tag{4.2}$$

where I_t is an indicator function that takes value 0 during the normal period and 1 during a crisis period. The coefficient $a_{2,i}$ captures the changes in global systematic risk exposure during the crisis period.

Policy intervention in the financial system during crisis periods is often specifically designed to reduce an individual country's global systematic risk exposure. If the policy measures were effective, then the global systematic risk exposure of a given banking market may have been reduced during the crisis instead of increased.[3] This is akin to the debate around whether increased international financial integration may or may not contribute to increased output correlation (Kalemli-Ozcan et al., 2013).

The existing literature suggests that US shocks have a significant influence on other economies during calm periods, reflecting its market leadership in many segments of the economy, its influence in portfolios and the position of the US dollar as a global reserve currency. Following Masson (1999), we denote these as *spillover effects*. However, during a period of stress, shocks from the crisis originating economy may impact over and above these spillovers, denoted as *idiosyncratic contagion*, (Dungey et al., 2005; Dungey and Martin, 2007). In the current chapter we denote the US banking sector as the crucible of the crisis and consider the evidence for idiosyncratic contagion from the US to other markets. Finally, Forbes and Rigobon (2002) argue that a crisis may bring a structural shift in the existing relationships above and beyond that accounted for by structural breaks in factor relationships, potentially attributable to herd behavior amongst investors which does not depend on economic fundamentals (Bekaert et al., 2014).[4] Our

[3] However, the alternative to reduced global exposure is not necessarily proof of lack of policy efficacy as we do not have a true proxy of what the outcome would have been in the absence of policy actions.

[4] Bekaert et al. (2014) refer this as "herding contagion".

final levels specification captures each of these channels as follows:

$$r_{j,t} = b_{j,0}+b_{1,j}f_t^{global}+b_{2,j}f_t^{global}I_t+b_{3,j}f_t^{US}+b_{4,j}f_t^{US}I_t+b_{5,j}I_t+\xi_{j,t}; \quad j = 1, ..., n-1 \neq US \tag{4.3}$$

where the US factor, f^{US}, is extracted as the residual from applying Eq. (4.2) to $i = US$, thus orthogonalizing the global and US factors. In Eq. (4.3), the coefficient $b_{1,j}$ represents a standard CAPM beta coefficient against global markets, $b_{2,j}$ represents systemic contagion, $b_{3,j}$ measures the general spillover effects of US shocks, $b_{4,j}$ measures the *additional* effects of US shocks during the crisis period, that is idiosyncratic contagion and $b_{5,j}$ captures any intercept shift in the factor model representation or shift contagion during the crisis period.

4.2.2 The GARCH Framework and Measuring Volatility Contagion

Financial return series generally exhibit heteroskedasticity. To capture this we incorporate the exponential generalized autoregressive conditional heteroskedasticity (EGARCH) model of Nelson (1991), which has the advantage that it does not require non-negativity constraints on parameters. GARCH(1,1) is usually sufficient to capture the financial data properties (Engle, 1982; Hansen and Lunde, 2005). The variance equation of the EGARCH model (to accompany mean equations given in Eq. (4.1-4.3)) can be expressed as:

$$\begin{gathered} ln(\sigma_{i,t}^2) = c_{0,i} + c_{1,i}(|z_{i,t-1}| - E|z_{i,t-1}|) + c_{2,i}z_{i,t-1} + c_{3,i}ln(\sigma_{i,t-1}^2); \\ z_{i,t-1} = \eta_{i,t-1}/\sigma_{i,t-1}; \eta_{i,t} = \{e_{i,t}, \varepsilon_{i,t}, \xi_{j,t}\} \\ \eta_{i,t} \sim Student - t(0, \sigma_{i,t}^2). \end{gathered} \tag{4.4}$$

To capture the US volatility spillover effects in the variance equation of the non-US markets, the variance equation those markets takes the following form:

Table 4.1: List of banking markets considered

America		Europe	
1	Argentina	24	Austria
2	Brazil	25	Belgium
3	Canada	26	Bulgaria
4	Chile	27	Cyprus
5	Mexico	28	Czech Rep
6	Peru	29	Denmark
7	Venezuela	30	Finland
8	US	31	France
Asia		32	Germany
9	Australia	33	Greece
10	China	34	Hungary
11	Hong Kong	35	Ireland
12	India	36	Italy
13	Indonesia	37	Luxemburg
14	Israel	38	Malta
15	Japan	39	Netherlands
16	Korea	40	Norway
17	Malaysia	41	Poland
18	Pakistan	42	Portugal
19	Philippine	43	Romania
20	Singapore	44	Russia
21	Sri Lanka	45	Slovenia
22	Taiwan	46	Spain
23	Thailand	47	Sweden
		48	Switzerland
		49	Turkey
		50	UK

$$\begin{aligned} ln(\sigma^2_{j,t}) &= c_{0,j} + c_{1,j}(|z_{j,t-1}| - E|z_{j,t-1}|) + c_{2,j}z_{j,t-1} + c_{3,j}ln(\sigma^2_{j,t-1}) \\ &\quad +\pi_{1,j}ln(\hat{\sigma}^2_{us,t}) + \pi_{2,j}ln(\hat{\sigma}^2_{us,t})I_t; \quad j = 1, ..., n-1 \neq US. \end{aligned} \tag{4.5}$$

In Eq. (4.5) the parameter estimate $\pi_{1,j}$ captures the general US volatility spillover and $\pi_{2,j}$ captures *additional* US volatility spillover for market j during the crisis period which we denote as volatility contagion. The GARCH framework provided in Eq. (4.5) is motivated by Hamao et al. (1990); Edwards (1998); Iwatsubo and Inagaki (2007), amongst others.

4.2.3 Sample, Data and Crisis period

The data set comprise daily equity indices of banking sectors for 50 countries including the US for January 2, 2001 to May 8, 2009 available in Thompson Datastream. Table 4.1 provides the list of banking markets considered in this chapter.[5] The aggregate world banking sector index returns provide the global factor.[6] In line with existing literature we use two-day rolling moving averages to deal with differing time zones and asynchronous trading times as in Forbes and Rigobon (2002) and adjust time/date as Day 01 in US/Americas = Day 2 in Asia and Europe. As in Chapter 2, we define the crisis period endogenously using the Iterative Cumulative Sum of Square (ICSS) algorithm based on the CUSUM test to detect the structural change in variance of an individual return series (Inclan and Tiao, 1994; Sanso et al., 2004) and use the identified break in the US banking sector index return to determine the crisis period. Using this procedure the endogenously chosen crisis period is from July 19, 2007 to May 08, 2009. These dates are consistent with the existing literature, see Bekaert et al. (2014) and the extensive overview of dates provided in Dungey et al. (2013).

4.3 Contagion Results and Discussion

The resulting evidence for contagion is reported in Table 4.2. Almost all of the 49 individual banking markets have statistically significant and positive systematic comovement with the global banking market throughout the sample, evidenced by $b_1 \neq 0$, indicating exposure to global systematic risk. The parameter estimates support that the level of global integration is higher for advanced countries, con-

[5] Datastream provides banking sector equity index data for 59 countries; however, the data for some countries are not available for the whole sample periods, therefore, restricting our sample size to 50.

[6] The series used is Datastream mnemonic *bankswd*. The literature suggests that banking and insurance sectors have high level of global integration at sectoral level (Bekaert et al., 2009) and industry factors dominate country factors while explaining the equity returns (Cavaglia et al., 2000). The results are robust to the alternative of using the aggregate world equity index (*totmkwd*) as the global factor.

sistent with evidence in Laeven and Valencia (2013). These cross-border linkages may reflect both on and off balance sheet channels (Cetorelli and Goldberg, 2011; Sbracia and Zaghini, 2003).

The results provide evidence for the severity of disruptions in the 2007-2009 crisis. Exposure to the global systematic risk factor changed significantly for 29 of the 49 countries, that is $b_2 \neq 0$ as reported in Table 3, consistent with these markets experiencing systematic contagion during the crisis, and prior evidence on structural breaks in the relationship with global conditions during crisis periods (Dornbusch et al., 2000; Dungey et al., 2005). However, this evidence is strongly skewed towards the developing markets. Many of the advanced markets did not experience a structural break, that is, the hypothesis $b_2 = 0$ is not rejected in France, Greece, Italy, Malta, Norway, Portugal and the UK. We cannot distinguish here whether the policy actions undertaken were sufficient to offset any potential change, or whether no change was experienced. In Japan, Germany, the Netherlands, Spain, Sweden and Switzerland the results go further in that the hypothesis $b_2 < 0$ is not rejected. In these countries the potential for an increased factor loading (b_2) during the crisis observed in other jurisdictions was not present, and this may reflect that their policy initiatives were effective in suppressing the transmission of the crisis to the domestic banking system, in line with the findings of Ait-Sahalia et al. (2012).

Four countries did not have a significant link with the global factor during the pre-crisis period, that is $b_1 = 0$. This potentially reflects that each of these countries, Bulgaria, Peru, Sri Lanka, and Venezuela, is a relatively small and closed market. However, during the crisis, this was no longer the case for Peru and Bulgaria, ($b_2 \neq 0$) and they were exposed to global conditions, although Sri Lanka and Venezuela continued to remain isolated in this respect.

In addition to responding to global conditions, the majority of markets also experienced spillovers from the US during the non-crisis periods. Of the 49 markets 29 experienced idiosyncratic shock effects from the US banking market, ev-

Table 4.2: Parameter estimates and hypothesis testing results

SN	Country	Global exposure (b_1)	Systematic contagion (b_2)	Idiosyncratic contagion (b_4)	Structural shift (b_5)	Volatility contagion (π_2)	Chi-square test: Joint significance $b_2 = b_4 = 0$	$b_2 = \pi_2 = 0$	$b_4 = \pi_2 = 0$	$b_2 = b_4 = \pi_2 = 0$
	Panel A: No contagion									
1	Israel	0.297***	0.020	0.077	0.000	-0.003	2.26	0.27	2.02	2.35
2	Malaysia	0.256***	0.044	0.031	0.000	-0.005	3.31	2.45	1.47	3.79
3	Singapore	0.472***	-0.036	0.015	0.000	0.003	0.64	1.12	0.62	1.17
4	Taiwan	0.445***	-0.013	0.064	0.000	0.018	1.23	2.17	3.45	3.47
5	Venezuela	0.036	-0.008	0.019	0.000	-0.014	0.31	1.81	1.99	2.02
6	Hong Kong	0.511***	0.066**	0.027	0.001**	-0.002	4.79*	4.27	1.13	5.25
7	Hungary	0.578***	-0.045	0.150*	-0.003***	-0.001	3.79	0.35	3.50	3.82
	Panel B: Volatility contagion driven									
8	Indonesia	0.575***	0.000	0.100	0.000	0.039***	2.03	11.70***	13.61***	13.64***
9	Korea	0.880***	-0.111	0.078	-0.003***	0.077***	3.18	26.88***	25.60***	27.78***
10	Mexico	0.527***	0.009	-0.082**	0.000	0.062***	3.99	18.87***	22.68***	22.71***
11	Russia	0.380***	0.029	-0.016	-0.003***	0.026**	0.22	6.81**	6.66**	6.91*
12	Sri Lanka	0.010	0.027	0.004	-0.001***	0.056***	1.02	19.02***	18.09***	19.13***
	Panel C: Systematic contagion driven									
13	Canada	0.633***	0.212***	0.045	0.000	0.006	49.02***	46.00***	2.38	49.33***
14	Germany	0.703***	-0.195***	0.086	-0.001	0.001	12.67***	10.73***	2.62	12.84***
15	Peru	0.018	0.188***	-0.032	0.000	-0.013	67.10***	67.17***	2.41	67.72***
16	Spain	0.678***	-0.225***	0.027	-0.001	0.005*	18.55***	21.41***	3.07	21.72***
	Panel D: Idiosyncratic contagion driven									
17	Chile	0.519***	-0.051	0.101***	-0.001*	0.006	9.58***	2.65	8.20**	9.89**
18	France	0.673***	0.040	0.161***	-0.002**	0.001	8.02**	0.64	7.83**	8.07**
19	Greece	0.496***	0.082	0.200***	-0.001	0.007	16.68***	2.89	15.09***	18.12***
20	Italy	0.539***	-0.066	0.139***	-0.001*	0.001	10.72***	1.80	9.61***	10.98**
21	Malta	0.064***	0.005	0.102***	0.000	0.011	13.28***	1.08	13.94***	14.47***
22	Norway	0.491***	0.081	0.407***	-0.001	-0.002	34.87***	1.29	34.24***	35.35***
23	Poland	0.410***	0.089	0.140**	-0.002**	0.010	7.23**	2.55	5.39*	7.59*
24	UK	0.573***	0.063	0.246***	-0.002***	0.000	19.85***	1.13	18.92***	19.87***

(continued on next page)

Table 4.2 *continued*: Parameter estimates and hypothesis testing results

SN	Country	b_1	b_2	b_4	b_5	π_2	$b_2 = b_4 = 0$	$b_2 = \pi_2 = 0$	$b_4 = \pi_2 = 0$	$b_2 = b_4 = \pi_2 = 0$
25	Czech Rep	0.375***	0.124**	0.174***	0.000	-0.003	12.36***	4.21	7.03**	12.72***
26	Japan	0.716***	-0.095*	0.216***	0.000	0.002	14.90***	3.17	13.46***	15.03***
27	Portugal	0.316***	-0.016	0.255***	-0.003***	-0.016*	36.19***	3.45	41.10***	41.17***
	Panel E: Multiple drivers									
28	Austria	0.324***	0.328***	0.261***	-0.002**	-0.016	50.99***	30.44***	21.14***	51.97***
29	Belgium	0.558***	0.183***	0.259***	-0.002***	0.001	28.10***	7.94**	19.39***	28.19***
30	Cyprus	0.440***	0.233***	0.177***	0.000	0.005	24.63***	14.63***	9.48***	24.95***
31	Denmark	0.465***	0.088*	0.204***	-0.002***	0.012	20.14***	5.24*	18.35***	22.71***
32	Ireland	0.521***	0.356***	0.367***	-0.003***	-0.002	32.02***	15.75***	21.19***	32.54***
33	Netherlands	0.668***	-0.253***	-0.165***	-0.002**	-0.001	26.94***	16.43***	8.11**	26.96***
34	Pakistan	0.196***	-0.170***	0.136***	-0.002***	0.009	25.69***	20.60***	10.07***	27.81***
35	Philippines	0.315***	0.124***	0.126***	0.000	-0.016	22.73***	11.29***	10.23***	24.15***
36	Romania	0.165***	0.359***	0.227***	-0.002***	-0.019	64.26***	48.07***	18.37***	69.00***
37	Slovenia	0.050**	0.108***	0.147***	0.000	0.027	39.53***	15.21***	25.18***	41.64***
38	Switzerland	0.803***	-0.122**	0.128**	-0.002***	0.003	9.35***	5.45*	6.42**	10.57**
39	Argentina	0.544***	-0.193***	0.038	-0.002***	0.021**	19.78***	25.80***	6.40**	25.89***
40	Brazil	1.179***	-0.193***	-0.009	-0.001	0.035***	11.96***	22.55***	12.37***	22.69***
41	China	0.129***	0.121***	-0.018	0.000	-0.084***	7.10**	33.37***	25.60***	33.38***
42	Thailand	0.490***	-0.133**	0.037	0.000	0.047***	6.59**	14.77***	9.20**	14.99***
43	Australia	0.515***	0.217***	0.127***	-0.001	-0.022**	27.16***	23.46***	13.08***	33.70***
44	Finland	0.340***	0.114**	0.302***	-0.001	-0.035**	38.71***	0.64	7.83**	8.07**
45	India	0.443***	0.154**	0.255***	0.000	-0.036***	22.13***	13.78***	24.35***	32.20***
46	Bulgaria	0.049	0.388***	0.094*	-0.003***	-0.062***	49.55***	55.23***	12.94***	60.89***
47	Luxemburg	0.162***	0.118***	0.150***	-0.001***	-0.044***	34.91***	25.57***	29.56***	46.50***
48	Sweden	0.691***	-0.166**	0.263***	-0.002**	0.011**	22.04***	11.86***	21.75***	27.80***
49	Turkey	0.770***	-0.245**	0.205*	-0.001	0.047***	8.68**	23.57***	20.60***	25.64***
50	US	0.908***	0.268***		-0.002**					

Note: The values in column for b_1, b_2, b_4, b_5 and π_2 are the parameter estimates from Eqs. (4.3) and (4.5). The values for joint test are the Chi-square values. ***, **, and * indicate statistical significance at 1%, 5% and 10% respectively.

idenced by $b_3 \neq 0$. The notable exceptions are a mixture of advanced banking markets (Australia, Austria, Czech Republic, Denmark, Finland, Greece, Korea, Norway, Portugal and Taiwan) and emerging banking markets (China, Indonesia, Hungary, Malaysia, Poland, Sri Lanka, Thailand, Turkey and Venezuela). When the estimate b_3 is negative it indicates the potential for portfolio diversification benefits relative to the US, which is the case for a mixture of advanced markets such as Japan, Luxembourg, Malta and Slovenia and emerging markets such as Brazil, Chile, India, Pakistan and Philippines. However, this effect appears to be dampened during the crisis, as the US idiosyncratic effects have an overwhelmingly positive transmission to these markets. The hypothesis $b_3 + b_4 = 0$ is not rejected in most of these markets. The Brazilian and Peruvian markets appear to have consistently negative response to US originated shocks even during the crisis period, consistent with recent evidence that the Latin American banking market was little effected by the GFC (Kamil and Rai, 2010; Ocampo, 2009).

Almost all of the banking sectors show evidence of volatility spillover effects during the non-crisis period, supporting the contention that the inclusion of volatility transmission is important in the model specification.[7] During the non-crisis period the countries which do not experience volatility spillovers are two Asian markets - China and Pakistan and two Latin American markets - Argentina and Peru. Clearly, the overall evidence presented here supports the banking sector in Peru as relatively isolated from international capital markets.

The crisis also caused a structural shift as specified in Eq. 4.3, that is $b_5 = 0$ is rejected for 23 of the 49 countries. Each of these countries also have evidence of a break in the structural parameters (b_2, b_4 or π_2). The evidence for structural shifts during the crisis period is consistent with the occurrence of herding behavior in addition to global shocks and the US idiosyncratic shocks during the GFC.

[7] The statistically significant parameter estimates for c_1 and c_2 for most of the markets support the EGARCH specification in Eq. (4.5).

4.3.1 Evidence of Contagion

Table 4.2 shows that almost all of the 49 banking markets in the sample experienced some form of contagion from the US. The null of no contagion in any form - systematic, idiosyncratic or volatility - given by the joint test for $b_2 = b_4 = \pi_2 = 0$, is rejected in most cases.[8] The exceptions are Hong Kong, Hungary, Israel, Malaysia, Singapore, Taiwan and Venezuela. These markets are generally small economies although with a great variety of exposure to international markets. Israel, for example, is an isolated small developed market. The exception is Malaysia, a relatively large economy, which had built significant buffers in the aftermath of the Asian crisis of 1997-98, and a banking system with negligible exposure to the US sub-prime loan products (Khoon and Mah-Hui, 2010). Also in Asia, the financial hub of Singapore, had liquid and well capitalized domestic banks and foreign banks with liquidity assurance from their head office (a formal commitment required for licensing procedure) which reduced the exposure of the Singaporean banking sector to contagion. Hong Kong and Hungary represent somewhat different cases, in that the null hypothesis for the joint test ($b_2 = b_4 = \pi_2 = 0$) is not rejected but the null hypothesis for individual univariate tests of contagion effects are rejected. In the case of Hong Kong, the null of no systemic contagion $b_2 = 0$, is rejected. In the case of Hungary, the null of no idiosyncratic contagion, $b_4 = 0$, is rejected. Despite the overall evidence for no contagion, the Hong Kong banking sector displays sensitivity to global shocks (fundamentals), and the Hungarian banking sector to US idiosyncratic shocks. Our results for the banking sectors in these countries are consistent with the IMF Country Reports 2008 and 2009 for these countries which suggest that their banking sectors performed well during the crisis, an outcome often attributed in the discourse to effective policy initiatives.

[8] We also consider potential joint tests incorporating b_5, such as $b_2 = b_4 = b_5 = \pi_2 = 0$; $b_2 = b_4 = b_5 = 0$. The results are similar as b_5 is always accompanied some other contagion estimates (b_2,b_4, or π_2).

Figure 4.1: Univariate hypothesis test

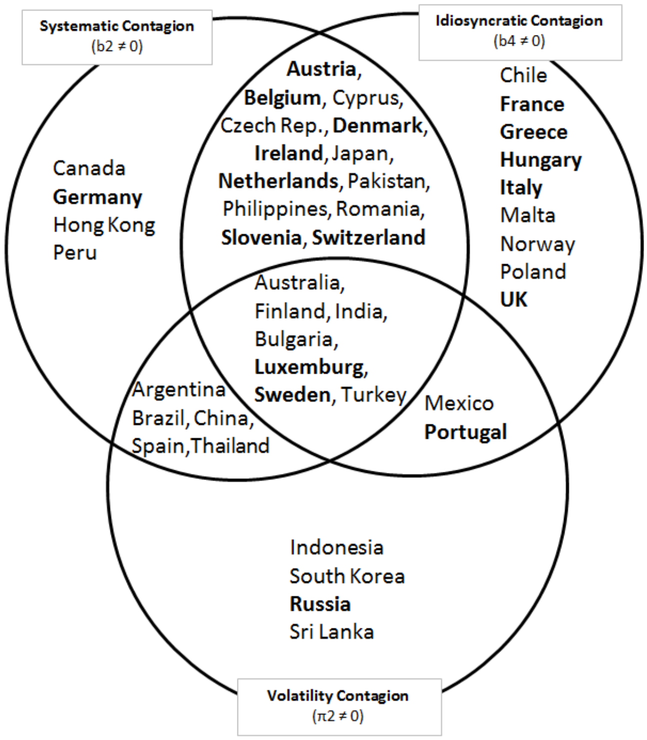


Figure 4.1 provides a schematic representation of the clustering of the different individual coefficient hypothesis testing results, for systematic contagion, idiosyncratic contagion and volatility contagion, providing a convenient means of discussion. The distinction between bold and plain text relates to the links to identified systemic banking crises to be discussed below.

4.3.1.1 Volatility Contagion

A small group of countries (Indonesia, Korea, Mexico, Russia and Sri Lanka) have contagion effects driven largely by volatility contagion. These countries do not have level effects, that is, no evidence of either systematic contagion or idiosyncratic contagion.[9] With the exception of Sri Lanka, the countries in this group are markets which were involved in financial crises during the 1990s and might have learned from that experience. However, the high level of market uncertainty caused by the GFC resulted in increased market volatility in these

[9]When we look at univariate hypothesis testing, however, the null for no idiosyncratic contagion ($b_4 = 0$) is rejected for Mexico

countries. The literature suggests that the banking systems in Indonesia and Korea particularly were relatively healthy and had less exposure to US sub-prime products (IMF, 2009b,c). In the case of Mexico, although the aggregate economy was hit hard, the banking sector was relatively resilient during the crisis (IMF, 2009d).

4.3.1.2 Systematic Contagion

A further small group of countries (Canada, Germany, Peru and Spain) have evidence of contagion effects driven largely by systematic contagion. These are large advanced economies (except Peru which is a small closed economy) with strong international banking linkages. It may be that these linkages are sufficient to enable systematic contagion to affect the domestic markets. None of these markets experienced idiosyncratic contagion. Despite the fact that the German banking sector experienced huge losses - about 57 percent of stock market capitalization for banking sector stocks - and German banks were highly involved in asset backed securities, we do not find a statistically significant result for idiosyncratic contagion from the US to Germany. The German banking system forms the basis of its capital markets, and during the crisis German banks faced problems with leverage, liquidity and funding (Acharya and Schnabl, 2010).

In Spain the direct impact of the crisis on the banking sector was limited as the banks had a retail-oriented business model and negligible exposure to US subprime mortgages (Acharya and Schnabl, 2010; IMF, 2009e). However, when the crisis spread to the global financial conditions and the real sector, the crisis was transmitted to the Spanish banking sector through common conditions such as tighter liquidity. The Spanish banking sector additionally experienced volatility contagion in response to the higher turmoil in the US markets.

In the case of the Canadian banking system, despite its close proximity to US (with strong real and financial linkages), it avoided crisis effects. Canadian banks follow relatively conservative banking practices with strong prudential regulation, and consequently had lower exposure to sub-prime effects than the US (IMF, 2009f).

4.3.1.3 Idiosyncratic Contagion

In about one-fifth of the countries US idiosyncratic shocks played a dominant role during the crisis. Countries in this group have a high level of global integration, are advanced and relatively large European countries (Czech Republic, France, Greece, Italy, Malta, Norway, Poland, Portugal, and UK) and Japan and Chile. Countries in this group did not generally experience systematic contagion (except Czech Republic and Japan) or volatility contagion (except Portugal). Since the banking fundamentals of these countries were generally strong (Chile, Japan, France, and Italy), and banks follow a traditional retail business model, these banking systems were relatively resilient to the crisis. Consequently, the large drop in the banking sector returns during the crisis was directly attributable to the idiosyncratic shocks originating in the US banking sector.

4.3.1.4 Multiple Drivers

The final group consists of all those countries where the null of joint hypotheses (bivariate and multivariate test) is rejected in all cases. All the countries in this group experience systematic contagion and the majority of the countries are part of the European Union. Seven countries (Australia, Finland, India, Luxemburg, Romania, Sweden and Turkey) have all effects, that is the null hypothesis is rejected in univariate, bivariate and multivariate hypothesis tests. Five countries (Argentina, Brazil, Bulgaria, China, and Thailand) have no idiosyncratic contagion from the US (univariate test) and 10 countries (Austria, Belgium, Cyprus, Denmark, Luxemburg, Netherlands, Pakistan, Philippines, Slovenia, and Switzerland) have no volatility contagion.

4.4 Contagion and the Systemic Banking Crises

4.4.1 Contagion and the Cost of Crisis

We couple the evidence for contagion in the banking system with the data for systemic banking crises provided in Laeven and Valencia (2013) to address the relationships between channels of contagion and the presence and cost of banking crises. Of the 41 banking markets in our sample which experienced contagion in any form, 18 banking markets experienced a banking system crisis during the GFC as documented in Laeven and Valencia (2013). The average output loss for these countries is about 30 percent of GDP and the average fiscal cost is about 7 percent of GDP.[10]

Figure 4.1 highlights the countries classified by channels of contagion which experienced systemic banking crises in emphasized bold. The majority of the countries which experienced a banking crisis are clustered in two groups: either experiencing both idiosyncratic and systematic contagion (Austria, Belgium, Denmark, Ireland, Netherlands, Slovenia, Switzerland) or idiosyncratic contagion only (France, Greece, Hungary, Italy and the UK). Seven of 12 countries in the systematic and idiosyncratic contagion group experienced a banking crisis. Table 3 shows shows that the average output loss (as a proportion of GDP) for these countries was almost 34 percent, and when we exclude Switzerland, which experienced no output loss, this rises to around 39 percent. The standard deviation of the output loss in this group is high, at 34 percent. The five countries which experience a banking crisis with only idiosyncratic contagion have a similar output loss of 33 percent, but a much lower standard deviation of this loss at almost 9

[10] Laeven and Valencia (2013) consider a banking crisis as a systemic if (i) there is a financial distress (as indicated by bank runs, losses in banking system, and/or bank liquidations), and (ii) there is a policy intervention in response to significant losses in banking system. Output losses are computed as the cumulative sum of the differences between actual and trend real GDP over the crisis period. The fiscal costs are measured as the component of gross fiscal cost related to the restructuring of the financial sector including fiscal costs associated with bank recapitalization but excluding asset purchases and direct liquidity assistance from the Treasury. See Laeven and Valencia (2013) for details.

Table 4.3: Cost of systemic banking system crisis

	Output loss	Fiscal cost		Output loss	Fiscal cost
Systematic and idiosyncratic			*Idiosyncratic only*		
Austria	14	4.9	France	23	1
Belgium	19	6	Greece	43	27.3
Denmark	36	3.1	Hungary	40	2.7
Ireland	106	40.7	Italy	32	0.3
Netherlands	23	12.7	UK	25	8.8
Slovenia	38	3.6	Average	32.6	8.0
Switzerland	0	1.1	St. dev.	8.8	11.3
Average	33.7	10.3			
St. dev.	34.4	13.9	*Systematic and volatility*		
Average (excl. Swiss)	39.3	11.8	Spain	39	3.8
St. dev.	34.0	14.6			
			All forms of contagion		
Systematic only			Luxembourg	36	7.7
Germany	11	1.8	Sweden	25	0.7
			Average	30.5	4.2
Idiosyncratic and volatility			st dev	7.8	4.9
Portugal	37	0			
			Overall		
Volatility only			Average	30.4	7.1
Russia	0	2.3	St. dev.	23.0	10.6

Note: Output loss and fiscal cost are expressed in percent of GDP. Data source: (Laeven and Valencia, 2013)

percent. The other forms of contagion associate less strongly with banking crises than these two categories, with volatility contagion relatively unimportant.

The evidence from Figure 4.1 and Table 4.3 indicates that banking crises in this sample are frequently associated with idiosyncratic contagion - which tends to result in output loss. However, when this is coupled with the presence of systematic contagion, then there is great uncertainty about the output loss, in our sample the output loss for this group ranges from nothing in Switzerland to 106 percent of GDP in Ireland. In contrast, when only idiosyncratic contagion is associated with a banking crisis, the range for output loss is smaller, between 20 and 40 percent of GDP.

The fiscal costs associated with the countries in banking crisis do not show this distinction between the dominant types of contagion; the average fiscal costs are 8 percent or 10 percent of GDP for countries with both systemic and idiosyncratic contagion or idiosyncratic contagion only. These results point to the importance of understanding the source of contagion and its links to banking crises. For policy makers, it appears that the maximum uncertainty about the outcome of a banking crisis occurs when both idiosyncratic and systematic contagion affect the market.

4.4.2 Contagion, Industry Characteristics and the Systemic Crises

In this section we formalize the discussion from the previous section and examine the empirical evidence for the transmission of banking crises via different contagion channels incorporating industry characteristics as control variables using a Probit model as follows:

$$Pr(BankCrisis_i = 1) = \Phi(\gamma_o + X_i^{'}\lambda + W_i^{'}\theta + Z_i^{'}\delta) \tag{4.6}$$

where X_i is a vector of indicator variables representing the contagion measures identified in the Section 4.3, taking the value of 1 when that contagion channel is statistically significant in the Table 4.2 (we exclude the volatility channel as it is completely coincident with all occurrences and non-occurrences of crisis). W_i is a vector of banking industry characteristics, Z_i is a vector of macroeconomic control variables, λ, θ and δ are the vectors of weights on each of these effects, and Φ is the cumulative distribution function of a standard normal random variable. The data for banking industry characteristics and control variables are from Cihak et al. (2012) and available from World Bank website.[11] Motivated by Beck et al. (2006), Berger and Bouwman (2013) and Lepetit et al. (2008), we consider the market concentration ratio (given by the market share of the 3 largest banks), the bank capital ratio (ratio of regulatory capital to risk-weighted assets) and bank income structure (non-interest income to total income ratio) to characterize

[11] http://data.worldbank.org/data-catalog/global-financial-development

the banking industry.[12] We use the relative size of the banking sector (ratio of banking sector assets to GDP) and external debt exposure (ratio of total external debt outstanding to GDP) as macroeconomic control variables. The control variables are kept at their pre-crisis period average.[13] A detailed data description is provided in Cihak et al. (2012) or on the Global Financial Development Database of the World Bank website.

Three specifications of the model are presented in Table 4.4. Specification (1) presents the coefficient estimates and marginal effects where only contagion channels are present, specification (2) when only market control variables are applied and specification (3) the full specification with the full set of X, W, Z variables.

The probit model results reported in Table 4.4 support the hypothesis that idiosyncratic contagion is an important avenue for systemic banking crises. The presence of idiosyncratic contagion (a shock transmitted from the crisis originating country) increases the probability of systemic banking crisis in a country by almost 27 percent. The contribution of systematic contagion, however, is not statistically significant at conventional levels, suggesting that increased interdependence amongst banking sectors through global factor does not necessarily destabilize the domestic banking system. This does not necessarily mean that the potential for systematic contagion should be paid less attention by policy makers. The evidence suggests that policy issues taken during the global financial crisis contributed to reduced tail risk in the financial system (Ait-Sahalia et al., 2012; Gagnon et al., 2011; Klyuev et al., 2009). However, our results do suggest that there remains significant evidence that crises transmitted via idiosyncratic shocks may destabilize the domestic financial system, and policies designed to reduce the potential for idiosyncratic contagion may result in reduced impact on domestic

[12] For robustness, we consider the alternatives of the 5 largest banks based concentration ratio and the ratio of bank equity capital to total asset to proxy for bank capital. The results are very similar.

[13] The results are robust to keeping control variables at 2006 level.

Table 4.4: Probit model results

	Dependent variable (systemic banking crisis dummy)					
	(1)		(2)		(3)	
	estimate (se)	marginal effect	estimate (se)	marginal effect	estimate (se)	marginal effect
Systematic contagion#	-0.193	-0.065			-0.7235	-0.113
	(0.417)	(0.139)			-0.7566	(0.083)
Idiosyncratic contagion	1.113**	0.340***			1.853**	0.266**
	(0.516)	(0.126)			(0.768)	(0.137)
Shift contagion	1.342***	0.442***			0.914	0.168
	(0.450)	(0.125)			(0.669)	(0.169)
Market concentration			-0.0242*	-0.006	-0.0486*	-0.008*
			(0.015)	(0.004)	(0.025)	(0.004)
Regulatory capital/Risk-weighted asset			-0.4725***	-0.123***	-0.6304**	-0.109**
			(0.140)	(0.036)	(0.210)	(0.052)
Non-interest income/Total income			0.0513**	0.013**	0.0546**	0.009
			(0.023)	(0.006)	(0.026)	(0.008)
Banking assets/GDP			-0.0105	-0.003	-0.0082	-0.001
			(0.009)	(0.002)	(0.010)	(0.002)
External Debt/GDP			0.0648***	0.017***	0.0681***	0.012*
			(0.019)	(0.006)	(0.027)	(0.006)
Constant	-1.874		4.2703		5.9836	
	(0.594)		(1.960)		(3.486)	
	[0.002]		[0.029]		[0.086]	
N	49		44		43	
Wald Chi-sq (p-value)	11.84 (0.008)		34.18 (0.000)		25.82 (0.001)	
Pseudo R-sq.	0.308		0.594		0.706	

***, **, and * indicate significant at 1%, 5% and 10% level respectively.

#Here $b_2 > 0$ is considered systematic contagion because $b_2 < 0$ may suggest policy efficacy which help to financial stability.

economies.

We specifically test the hypotheses in the existing literature that larger, more concentrated banking sectors with lower engagement in shadow banking activities and higher regulatory capital will have lower probability of crisis occurrence (Acharya et al., 2010; Allen and Gale, 2000; Beck et al., 2006; Berger and Bouwman, 2013; Bretschger et al., 2012; Cole, 2012; De Jonghe, 2010; Lepetit et al., 2008; Miles et al., 2013; Mirzaei et al., 2013). The results indicate support for the hypothesis that higher regulatory bank capital reduces the likelihood of a systemic banking crisis by about 11 percent. However, higher market concentration results in only an economically small reduction in the probability of a crisis, statistically significant at the 10 percent level, providing only limited support for the hypothesis that market concentration decreases the systemic risk, and the size of the banking sector (given by the banking sector to GDP ratio) has no significant effect. While the results for the non-interest income to total income ratio variable are not uniformly significant, the marginal effects in specification (3) indicate that where the banking sector engages less in retail banking activities and more in shadow banking activities the probability of a systemic crisis is increased. Finally, the statistically significant (at 10 percent) marginal impact of the external debt to GDP ratio on the probability of banking crisis supports the hypothesised feedback loop between sovereign debt and banking crises (Acharya et al., 2014; Adler, 2012).

In summary, the results show that the existence of idiosyncratic contagion during a crisis provides a statistically significant contribution to increasing the probability of a banking crisis in the recipient country, of 27 percent. This is a substantial channel, and worthy of policymakers attention in their attempts to mitigate the effects of foreign sourced crises on domestic economies. The usual finding that good macroeconomic policy settings, such as influence the debt to GDP ratio, are confirmed. As the literature suggests, higher regulatory capital can play a significant offsetting role in reducing banking crises, but proposals around the size of the sector and relative engagement in shadow banking are economically significant determinants in this analysis.

4.5 Concluding Remarks

This chapter implements a CAPM based modeling framework that encapsulates several alternative channels of contagion and relates them to the observed evidence for banking crises for 50 countries during the 2007-2009 global financial crisis. We determine that banking crises are strongly positively related to evidence of idiosyncratic contagion channels from the crisis originating countries. Idiosyncratic contagion represents the unanticipated impact of shocks affecting the crisis originating asset, in this case the US banking sector, and transmitted to other banking sectors. It is differentiated from the transmission of common shocks which hit the global markets. The common shocks may originate in the US, but can be identified by their very commonality, which we denote as systematic contagion. It also differs from general shifts in the market conditions, known as shift contagion, and transmission via changes in market volatility, or volatility contagion. The framework implemented here distinguishes each of these four channels of contagion and finds that although there appears to be clustered evidence for effects of both systematic and idiosyncratic contagion on the probability of banking crises, statistically, only the links with idiosyncratic contagion are significant. It is entirely possible that this result partly arises from the efforts of policy makers around the globe to contain the systematic effects of the crisis, thus dampening the systematic channel.

Our results provide evidences for the severity of 2007-2009 crisis. Banking sectors across the world were disturbed by the crisis and were not immune to contagion effects. About 60 percent of the sample banking markets experienced a break in global systematic risk exposure, and about 60 percent of banking markets experienced idiosyncratic contagion originating from the US banking market. While most banking markets show evidence of volatility spillovers from the US banking markets during periods of market calm, only about 40 percent of sample banking markets experienced volatility contagion during the crisis. We established that evidence of a banking crisis seemed to be related to two clusters of economies - one which experienced both systematic and idiosyncratic crises, and one which experienced idiosyncratic contagion only. While the average output loss effect of banking crises on these two groups of countries was quite similar, at about one-third, the standard deviation of this loss was very different. The group of countries which experienced only idiosyncratic contagion were more likely to experience an average loss - that is the range of output loss experienced was much smaller than the countries where systematic contagion was also significant.

The idiosyncratic shocks channel is empirically an important link in transmitting shocks across international banking sectors, strongly related to the subsequent occurrence of a banking crisis in the recipient country. Concentrated banking sectors, strong regulatory capital requirements and a concentration in retail banking income help to reduce the likelihood of systemic crisis, consistent with the existing evidence. However, there is evidently more that can be done by policy in identifying and defusing the transmission of country specific idiosyncratic shocks that are potential sources of idiosyncratic contagion so as to reduce the costs of any consequent banking crises.

Chapter 5

Jump Risk in the US Financial Sector

5.1 Introduction

Recent advances in high frequency financial econometric techniques have opened new frontiers for measuring financial risk (Barndorff-Nielsen and Shephard, 2006; Huang and Tauchen, 2005; Todorov and Bollerslev, 2010). It is now empirically feasible to take advantage of financial data available every minute or even every second. This chapter uses these advances to measure the systematic risk of financial firms. From the risk management perspective, if we assume that idiosyncratic risks across firms are independent, what matters is the systematic risk. A small shock to the market may have a profound effect on an individual firm with a high systematic risk parameter. Acharya et al. (2010) argue that financial firms are less able to cope with a significant drop in equity prices than non-financial firms. This is one of the main reasons policy makers impose a high equity base on financial firms (Acharya et al., 2010). The recent financial crisis in the US has raised concerns about the risk absorption capacity of financial firms and consequently their contribution to the stability of financial system. This motivates the focus on financial firms in this chapter.

The capital asset pricing model (CAPM) provides the basic foundation for measuring systematic risk (Sharpe, 1964). Conventionally the systematic risk exposure of an asset is measured by beta - the magnitude of comovement of an individual stock return with respect to market returns. This measure has been widely used in practice (Graham and Harvey, 2001). However, this conventional beta does not separately account for the continuous and jump price process of the underlying assets. Merton (1976) suggests that the exclusion of jump processes in a stochastic price process for an asset may produce a systematic bias in the valuation of securities. Jarrow and Rosenfeld (1984) suggest that market portfolio contains a jump component. Recent literature confirms the importance of jumps in the stochastic price process (Huang and Tauchen, 2005; Jacod and Todorov, 2009). The systematic risk of a firm may vary when there is a discontinuity in the price process of the benchmark market portfolio; such discontinuities are often attributed to the unexpected arrival of news (shock) in the market. Therefore, decomposing systematic risk into systematic continuous risk and systematic jump risk is important as these two components may require different risk premia.[1]

We first detect the days on which jumps (price discontinuities) occur in a benchmark market portfolio and estimate the magnitude of these jumps for the US financial sector using the model-free approach postulated by Barndorff-Nielsen and Shephard (2006), Andersen et al. (2007) and Huang and Tauchen (2005). We create an equally weighted index for the financial sector as a benchmark portfolio. We then adopt the approach of Todorov and Bollerslev (2010) to estimate systematic risk (beta) for both continuous and jump components using 5-minute transactions for a panel of 73 financial institutions (FIs) which are constituents of the S&P 500 over the the period of 2003-2011. These financial firms include banks (depositories), broker-dealers, insurers, real estate investment trusts (RE-

[1]Eraker et al. (2003) argue that jump component requires relatively larger risk premia than continuous component because jumps generate the large crash-like movements. Pan (2002) also finds evidence for large jump risk premia and Yan (2011) confirms that jump risk is priced in expected stock return.

ITs) and other financial institutions. We focus on estimating the time-varying systematic risk exposures of each firm in these categories.

The literature suggests that similar responses to jumps across financial firms may lead to a potential inherent systemic risk in the aggregate financial system (Acharya et al., 2012; Das and Uppal, 2004; de Bandt and Hartmann, 2000; Nicolo and Kwast, 2002). In this chapter, we formalize how systematic jump responses are related to the systemic risk of financial firms. As our sample consists of large US financial firms including the systemically important financial institutions (SIFIs) identified by the Financial Stability Board (FSB), this provides grounds to explore relationship between these two risk measures. Theoretically, systematic and systemic risk measures are interrelated. Systematic jump risk measures the magnitude of response of an individual financial firm to an unexpected but significant news shock in the financial sector index, whereas systemic risk measures a financial firm's overall contribution to systemwide failure. In other words, systematic jump risk is the market risk of an individual firm, whereas systemic risk is an individual firm's risk to the overall market (system).

Acharya et al. (2010) provide a framework to measure the contribution of each financial firm to systemic risk focusing on expected capital shortfall of the financial firms. Under this framework the systemic expected capital shortfall is measured as the amount by which a financial institution is undercapitalized when the overall financial system is undercapitalized. Financial institutions with higher expected capital shortfalls contribute most to the overall financial sector undercapitalization, and hence they are more systemically risky. Dungey et al. (2012) provide a measure of systemic risk determined by the interconnectedness amongst firms; a firm is systemically risky if it is strongly connected to many other firms; and if its strongest linkages are with other systemically risky firms. We extend this chapter by examining the relationship between systematic jump risk and systemic risk measures of Acharya et al. (2010) and Dungey et al. (2012).

Our results show that the inclusion of jumps in price processes is important - of the 108 months in our sample we observe at least one jump in each of 70 months. The average magnitude of jump beta is higher than that of the continuous beta and this measure is relatively smaller for the crisis-period compared with the pre-crisis period. At sub-sectoral level banks tend to have lower systematic risk exposure than broker-dealers but higher than insurers. However this pattern is time-varying. Our results further reveal that financial institutions with higher capital shortfall systemic risk tend to have higher response to jumps whereas more interconnected financial institutions tend to have lower response to jumps, and more highly leveraged and small firms are more responsive to jumps in the market than their counterparts.

The rest of the chapter is organized as follows: Section 5.2 elaborates the jump detection methodology and the Todorov and Bollerslev (2010) non-parametric approach to estimating continuous and jump beta, Section 5.3 explains the sample and data, Section 5.4 presents the results and Section 5.5 concludes the chapter.

5.2 The Methodological Framework

5.2.1 Identifying Jumps

This section briefly describes the jump detection methodology advanced by Barndorff-Nielsen and Shephard (2004, 2006). The log-price (p_t) process of an asset at time t can be represented by a stochastic differential equation as follows

$$dp_t = \alpha_t dt + \sigma_t dW_t + \kappa_t dJ_t, \tag{5.1}$$

where α_t is the time-varying drift of price process, σ_t is the time-varying volatility component, W_t is standard Brownian motion, J_t is a jump process and κ_t is the size of the jump at time t. The counting process $dJ_t = 1$ if there is a jump at time t, otherwise 0.

Intra-day returns are defined as follows:

$$r_{t,s} = p_{t,s} - p_{t,(s-1)} \tag{5.2}$$

where $r_{t,s}$ refers to s^{th} intra-day return on day t. The sampling frequency is such that $\Delta s < t$, resulting into n number of intra-day returns. For example, Δs may refer to 5 minutes.

Barndorff-Nielsen and Shephard (2004) provide two measures of the quadratic variation process - realized variance (RV) and bi-power variation (BV), which converge uniformly to different measures of the underlying jump-diffusion process as the sampling frequency increases,

$$RV_t \equiv \sum_{s=1}^{n} r_{t,s}^2 \xrightarrow{p} \int_{t-1}^{t} \sigma_s^2 ds + \int_{t-1}^{t} \kappa_s^2 dJ_s \tag{5.3}$$

$$BV_t \equiv \frac{\pi}{2} \frac{n}{n-1} \sum_{s=1}^{n} |r_{t,s}||r_{t,(s-1)}| \xrightarrow{p} \int_{t-1}^{t} \sigma_s^2 ds. \tag{5.4}$$

In the absence of jumps, the difference between RV and BV is zero (Tauchen and Zhou, 2011). If there are jumps, then

$$RV_t - BV_t \rightarrow \int_{t-1}^{t} \kappa_s^2 dJ_s. \tag{5.5}$$

Since the squared jumps calculated from Eq.(5.5) may be negative, Andersen et al. (2007) suggest truncating the actual empirical measurement at zero,

$$J_t \equiv max[RV_t - BV_t, 0]. \tag{5.6}$$

Barndorff-Nielsen and Shephard (2006) and Tauchen and Zhou (2011) suggest a ratio statistic,

$$RJ_t = \frac{RV_t - BV_t}{RV_t}, \tag{5.7}$$

which, in the absence of jumps, converges to a standard normal distribution when scaled by its asymptotic variance. That is, if no jumps occur on day t, then

$$ZJ_t = \frac{RJ_t}{\sqrt{\frac{1}{n}\left\{\left(\frac{\pi}{2}\right)^2 + \pi - 5\right\} max\left(1, \frac{DV_t}{BV_t^2}\right)}} \xrightarrow{d} N(0,1), \tag{5.8}$$

where DV_t is the quad-power variation robust to jumps as shown in Barndorff-Nielsen and Shephard (2004) and Andersen et al. (2007). The quad-power variation is approximated by

$$DV_t \equiv n\left(\frac{\pi}{2}\right)^2 \sum_{s=4}^{n} |r_{t,s}||r_{t,(s-1)}||r_{t,(s-2)}||r_{t,(s-3)}|. \tag{5.9}$$

The rejection of null of no jumps in Eq. (5.8) provides evidence of jumps in a stochastic price process for a given day based on given intra-day high-frequency returns. Huang and Tauchen (2005) show that this test has excellent size and power properties and is quite accurate in detecting jumps.

5.2.2 Estimating Systematic Risks: Continuous and Jump Betas

The systematic risk, β, of an individual stock can be estimated using a conventional CAPM framework as $\beta_i = cov(r_i, r_m)/var(r_m)$, and can be represented in market model form as follows:

$$r_{i,t,s} = \alpha_i + \beta_i r_{m,t,s} + e_{i,t,s} \tag{5.10}$$

where $r_{i,t,s}$ is the intra-day returns on an individual asset and $r_{m,t,s}$ is the intra-day returns on the aggregate market at time t. The slope coefficient β_i in Eq. (5.10) measures the magnitude of the comovement of stock returns with respect to market return and is the measure of systematic risk of an asset. The intensity of this systematic risk exposure may vary when the price follows a continuous and jump process (Merton, 1976; Todorov and Bollerslev, 2010), and therefore can be decomposed as continuous systematic risk exposure and jump risk exposure as follows:

$$r_{i,t,s} = \alpha_i + \beta_i^C r_{m,t,s}^C + \beta_i^J r_{m,t,s}^J + e_{i,t,s} \tag{5.11}$$

where β_i^C, and β_i^J measure the systematic risk associated with continuous and jump movements in the market returns (r_m^C and r_m^J) respectively. If the systematic risks of a firm to both movements are identical, that is, $\beta_i^C = \beta_i^J$ then Eq. (5.11) is equivalent to Eq. (5.10). However, the literature suggests that this is not the case (Eraker, 2004; Pan, 2002; Yan, 2011). Recently, Todorov and Bollerslev (2010) have provided a non-parametric approach to estimate β_i^C, and β_i^J.

Suppose that the stochastic log-price processes for market portfolio ($dp_{m,t}$) and individual stock ($dp_{i,t}$) take the following forms:

$$dp_{m,t} = \alpha_{m,t}dt + \sigma_{m,t}dW_{m,t} + \kappa_{m,t}dJ_{m,t} \tag{5.12}$$

$$dp_{i,t} = \alpha_{i,t}dt + \beta_i^C \sigma_{m,t}dW_{m,t} + \beta_i^J \kappa_{m,t}dJ_{m,t} + \sigma_{i,t}dW_{i,t} + \kappa_{i,t}dJ_{i,t}, \tag{5.13}$$

where the notations α_t, σ_t, W_t, J_t, and κ_t are as defined in Eq (5.1), with subscripts m and i referring to the aggregate market portfolio and individual stock respectively.

As advanced in Todorov and Bollerslev (2010), Eq. (5.12) and (5.13) provide non-parametric representations of β_i^C, and β_i^J using multipower covariation/variation between the price processes of individual stocks and the market portfolio for given continuous and jump components respectively. From the continuous components, we can estimate the continuous beta as follows:

$$\beta_{i,t}^C = \frac{\sum_{s=1}^n r_{i,t,s} r_{m,t,s} I}{\sum_{s=1}^n r_{m,t,s}^2 I}, \tag{5.14}$$

where I is an indicator function,

$$I = \begin{cases} 1 & if\ |r_{t,s}| \leq \theta \\ 0 & otherwise \end{cases}, \tag{5.15}$$

based on the the truncation threshold, θ, for continuous component. And from the jump components, we can estimate the jump beta as follows:

$$\begin{aligned} \beta^J_{i,t} &= sign\left\{\sum_{s=1}^{n} sign\{r_{i,t,s}r_{m,t,s}\}|r_{i,t,s}r_{m,t,s}|^{\tau}\right\} \\ &\times \left(\frac{|\sum_{s=1}^{n} sign\{r_{i,t,s}r_{m,t,s}\}|r_{i,t,s}r_{m,t,s}|^{\tau}|}{\sum_{s=1}^{n}|r_{m,t,s}|^{2\tau}}\right)^{1/\tau}, \end{aligned} \tag{5.16}$$

where τ is a positive number greater than or equal to 2 (Ait-Sahalia and Jacod, 2012; Todorov and Bollerslev, 2010). The sign in Eq. (5.16) is taken simply to retain the sign of the jump beta that may be distorted while taking absolute values. Todorov and Bollerslev (2010) show that the estimator in Eq. (5.16) converges to true jump beta when there is at least one significant jump in the market portfolio for the given estimation window.

An important aspect of estimating β_i^C and β_i^J is determining the continuous and jump components in price processes. To do so Todorov and Bollerslev (2010) suggest using different thresholds. The threshold for the continuous price movement is $\theta = \alpha_t^C \left(\frac{1}{n}\right)^{\omega}$ where $\omega \in (0,\, 0.5)$ and $\alpha_t^C = 3\sqrt{BV_t}$ suggesting that the continuous component discards only those returns which are more than three standard deviations away from mean, and unlikely to be associated with continuous price movements (Todorov and Bollerslev, 2010). On the other hand the threshold for the jump price movement is $|r_{t,s}| > \alpha_t^J \left(\frac{1}{n}\right)^{\omega}$ where $\alpha_t^J = 2\sqrt{BV_t}$ suggesting that the jump component discards only those returns which are within two standard deviations from the mean, and are most likely to be associated with continuous price movements.[2] In line with existing literature, this chapter defines

[2]The choice of threshold level may vary. For example, Alexeev et al. (2014) do not use a threshold for point estimate of β_i^J but use $\alpha_t^J = \sqrt{BV_t}$ while estimating the asymptotic variance of β_i^J. However, when we set $\tau \geq 2$, the continuous movements do not affect estimated jump

the thresholds as $\alpha_t^C = 3\sqrt{BV_t}$ for β_i^C as in Todorov and Bollerslev (2010) and no threshold for β_i^J as in Alexeev et al. (2014).

5.3 Sample and Data

We consider US financial sector stocks for the period of January 2003 to December 2011. We initially select 77 financial firms comprising banks, insurance, broker-dealers and other financial institutions from the S&P 500 high frequency dataset compiled in Dungey et al. (2012). Of these, we remove ACE, which is a Swiss insurance company, XL Capital, which is an Irish insurance company, Loews Corp, which is a conglomerate of banks, hotels and other non-financial business and Weyerhaeuser, which is a private owner of large timber lands in Canada. Our final sample consists of 5-minute transactions prices (returns) on these 73 financial firms listed in Table 5.3. We sub-divide the sample into 5 groups representing sub-sectors within the financial sector: banks, dealers-brokers, insurers, REITs and 'others'.

We use the 5-minute based high-frequency data for sample firms extracted from Thompson Reuters Tick History provided by SIRCA. Our intra-day data starts from 9:30 am and ends at 4 pm. We exclude overnight returns. Thus we have 78 intra-day observations for 2262 active trading days over a 9 year period (108 months). The use of a 5-minute sampling frequency helps tradeoff between microstructure noise and variance-bias (Andersen et al., 2007; Tauchen and Zhou, 2011).

We create an equally weighted index for the financial sector comprising these 73 firms over the sample period. The literature suggests that stock returns respond more to sectoral effects or news compared with aggregate equity market news, so that financial firms should respond more to financial sector news. Regulation of the financial sector also provides a potential avenue for common effects.

beta asymptotically.

Table 5.1: List of sample financial firms

SN	CODE	Banks
1	BAC	Bank of America Corporation
2	BBT	BB&T Corporation
3	BK	The Bank of New York Mellon Corp.
4	C	Citigroup, Inc.
5	CMA	Comerica Incorporated
6	COF	Capital One Financial Corp.
7	FHN	First Horizon National Corporation
8	FITB	Fifth Third Bancorp
9	HBAN	Huntington Bancshares Incorporated
10	HCBK	Hudson City Bancorp, Inc.
11	JPM	JPMorgan Chase & Co.
12	KEY	KeyCorp
13	MTB	M&T Bank Corporation
14	NTRS	Northern Trust Corporation
15	PBCT	Peoples United Financial Inc.
16	PNC	PNC Financial Services Group Inc.
17	RF	Regions Financial Corp.
18	SNV	Synovus Financial Corp.
19	STI	SunTrust Banks, Inc.
20	STT	State Street Corp.
21	USB	U.S. Bancorp
22	WFC	Wells Fargo & Company
23	ZION	Zions Bancorp.

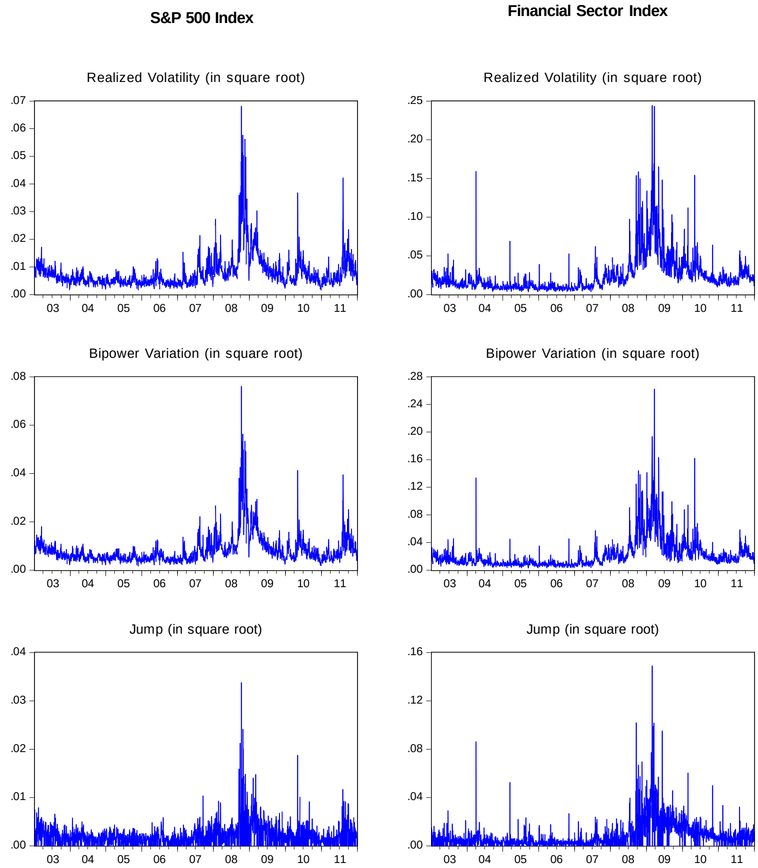
SN	CODE	Broker-Dealers
1	ETFC	E-TRADE Financial Corporation
2	GS	The Goldman Sachs Group, Inc.
3	LEH	Lehman Brothers
4	MS	Morgan Stanley
5	TROW	T. Rowe Price Group, Inc.

SN	CODE	Insurance
1	AFL	AFLAC Inc.
2	AIG	American International Group, Inc.
3	AIZ	Assurant Inc.
4	ALL	The Allstate Corporation
5	CB	The Chubb Corporation
6	CINF	Cincinnati Financial Corp.
7	GNW	Genworth Financial Inc.
8	HIG	Hartford Financial Services Group
9	LNC	Lincoln National Corp.
10	MBI	MBIA Inc.
11	MET	MetLife, Inc.
12	MMC	Marsh & McLennan Companies, Inc.
13	MTG	MGIC Investment Corp.
14	PFG	Principal Financial Group Inc.
15	PGR	Progressive Corp.
16	PRU	Prudential Financial, Inc.
17	TMK	Torchmark Corp.
18	UNM	Unum Group

SN	CODE	REITs
1	AIV	Apartment Investment & Management
2	AVB	Avalonbay Communities Inc.
3	BXP	Boston Properties Inc.
4	DDR	DDR Corp.
5	EQR	Equity Residential
6	GGP	General Growth Properties
7	HCN	Health Care REIT, Inc.
8	HCP	HCP, Inc.
9	KIM	Kimco Realty Corporation
10	PCL	Plum Creek Timber Co. Inc
11	PLD	Prologis, Inc.
12	PSA	Public Storage
13	SPG	Simon Property Group Inc.
14	VNO	Vornado Realty Trust
15	VTR	Ventas, Inc.

SN	CODE	Others
1	ACAS	American Capital, Ltd.
2	AXP	American Express Company
3	BEN	Franklin Resources Inc.
4	BLK	BlackRock, Inc.
5	CBG	CBRE Group, Inc
6	CME	CME Group Inc.
7	EFX	Equifax Inc.
8	FII	Federated Investors, Inc.
9	JNS	Janus Capital Group, Inc.
10	LM	Legg Mason Inc.
11	NDAQ	Nasdaq OMX Group Inc.
12	SLM	SLM Corporation

Figure 5.1: Realized volatilties, bipower variations and jumps



5.4 Results

5.4.1 Volatility Measures and Jumps

Figure 5.1 shows the daily realized volatility measures - realized volatility, bipower variation and jumps in square root form (standard deviation) for the S&P 500 index and equally weighted financial sector index. The market volatilities are relatively stable before the global financial crisis and increase during the crisis period, reaching a peak during the collapse of the Lehman Brothers in September 2008. The figure also reveals that the magnitude of volatilties and jumps in financial sector index is more than three times larger than that for S&P 500 index. The heightened and prolonged volatilities in the US financial sector after the collapse of Lehman Brothers is clearly evident in the figure for financial sector index returns, while this is not the case for S&P 500 index returns. These results

Table 5.2: Summary statistics for daily US financial sector volatilities and jumps

	RV_t	$\sqrt{RV_t}$	BV_t	$\sqrt{BV_t}$	J_t	$\sqrt{J_t}$
Mean	0.284	0.383	0.242	0.353	0.045	0.127
Median	0.073	0.271	0.064	0.252	0.006	0.075
St. dev.	0.819	0.370	0.726	0.343	0.192	0.171
Skewness	8.698	3.303	10.175	3.427	15.644	3.968
Kurtosis	115.31	18.90	171.38	20.76	360.47	30.76
Min.	0.003	0.058	0.003	0.051	0.000	0.000
Max.	15.017	3.875	17.314	4.161	5.589	2.364
$LB(Q-stat)_{10}$	2138	4226	1863	4041	572	1695
Observations	2262	2262	2262	2262	2262	2262

support our choice of equally weighted financial sector index as a benchmark portfolio to estimate continuous and jump betas.

Table 5.2 presents summary statistics for daily volatilties and jumps for the financial sector index. These statistics are based on annualized daily measures. The average realized volatility ($\sqrt{RV}$) is about 38.3%, whereas the bipower variation ($\sqrt{BV}$) is about 35.3%. The average absolute size of jump $\sqrt{J}$ is about 12.7%. Jiang and Yao (2013) report a similar jump size for US stocks - the mean jump size is about 14.14% and median jump size is about 11.74%. The variance decompositions in Eq.(5.5) and (5.6) indicate that the proportion of variance generated by the continuous returns component is about 85% ($\approxeq$ 0.242/0.284) and the jump returns component is about 15% ($\approxeq$ 0.045/0.284).[3] The Ljung-Box portmanteau statistics for these series suggest a high degree of serial correlation for up to tenth order. The results suggest the persistency and long memory characteristics of volatility.

The bottom panels of Figure 5.1 reveal that many of the largest realized volatilities are associated with jumps in the underlying price process. When we apply the Barndorff-Nielsen and Shephard (2006) approach to test for jumps at 0.1% significance level, over the sample period of 9 years, we observe at least one significant jump in 87 days in the S&P 500 index, and in 70 days in equally weighted financial sector index. Bollerslev et al. (2013) suggest that the presence

[3] Truncation of J_t in Eq. (5.6) makes some statistical discrepancy for $RV = BV + J$.

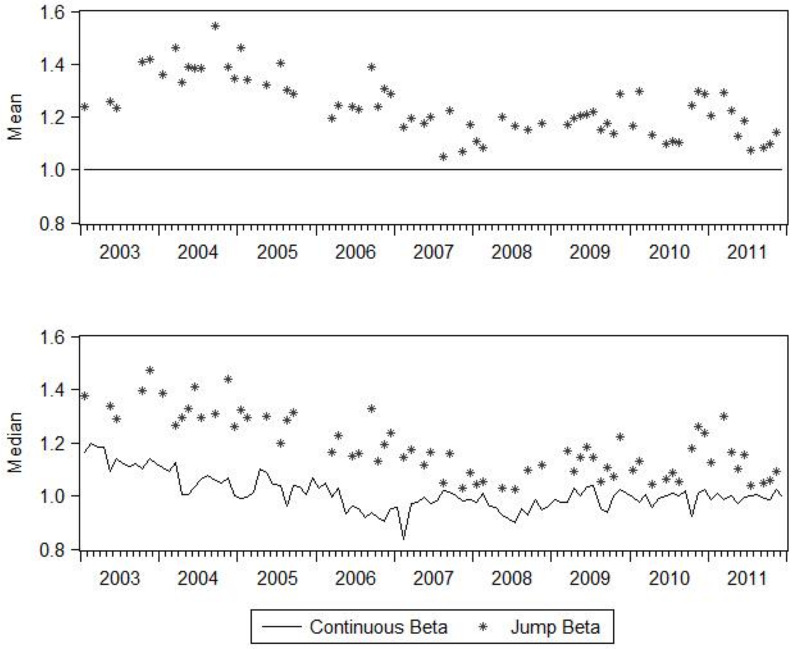
of jumps may vary across sectors (industries). While looking at the identified jump days in the financial sector index, we do not find any significant jumps in September 2008, a month with heightened market uncertainty including the bailout of AIG and collapse of Lehman Brothers. Since the financial sector is more volatile than the aggregate market during the crisis period, finding a smaller number of jumps for the overall sample period and no jumps in September 2008 using the financial sector index as the benchmark portfolio suggests that market uncertainties may have masked the arrival of new information for the financial sector. Patton and Verardo (2012) argue that investors revise their expectations of the aggregate economy as a result of the arrival of new information in the market. But when market uncertainty is high, which is a common feature of financial markets during the crisis period, gathering and processing information could be difficult and costly, and disturb the evolution of investors' learning process. As a result, even strong market news may not lead to a large and significant jump in the price process. Fewer jumps during crisis periods is a common finding in the literature (Chatrath et al., 2014; Alexeev et al., 2014).

Motivated by these identified jumps (with their corresponding months), we now estimate monthly continuous systematic risk (continuous beta) and jump systematic risk (jump beta) for the sample period. More specifically, we follow Todorov and Bollerslev (2010) and estimate these betas for each firm in our sample. We then link our results for systematic risk to systemic risk measures suggested in Acharya et al. (2010) and Dungey et al. (2012).

5.4.2 The Systematic Risk Exposure of Financial Firms

Figure 5.2 illustrates the cross-sectional average of monthly betas (continuous and jump) over the sample period. The average (mean) cross-sectional continuous beta of financial firms is 1 as our benchmark portfolio is the equally weighted returns of financial firms in our sample. The cross-sectional average (both mean

Figure 5.2: Cross-sectional average continuous and jump betas



and median) jump beta of financial firms however is greater than continuous beta. The average size of jump beta is 1.24 over the sample period which is consistent with results from the literature that jump betas are larger in magnitude than continuous betas (Alexeev et al., 2014; Todorov and Bollerslev, 2010). The larger jump beta, therefore suggests that financial firms are exposed to significant price discontinuities in price process of market portfolio, consistent with the argument that the systematic risk of firms increases in a response to new information shock in the market (Patton and Verardo, 2012).

To characterize the betas in Figure 5.2, and to aid our discussion, we split the sample period into pre-crisis (before July 2007), crisis (July 2007 to May 2009) and post-crisis (June 2009 onwards) periods.[4] Figure 5.2 shows that the average mean and median jump betas decreased gradually over the sample period, falling from 1.24 in pre-crisis period to 1.15 in the crisis period and then picking up slightly to 1.18 during the post-crisis period (see Table 5.3 Panel B first row). Caporale (2012) also find that the systematic risk of banks started

[4]We use the crisis period identified in Chapter 2

Table 5.3: Continuous and jump betas

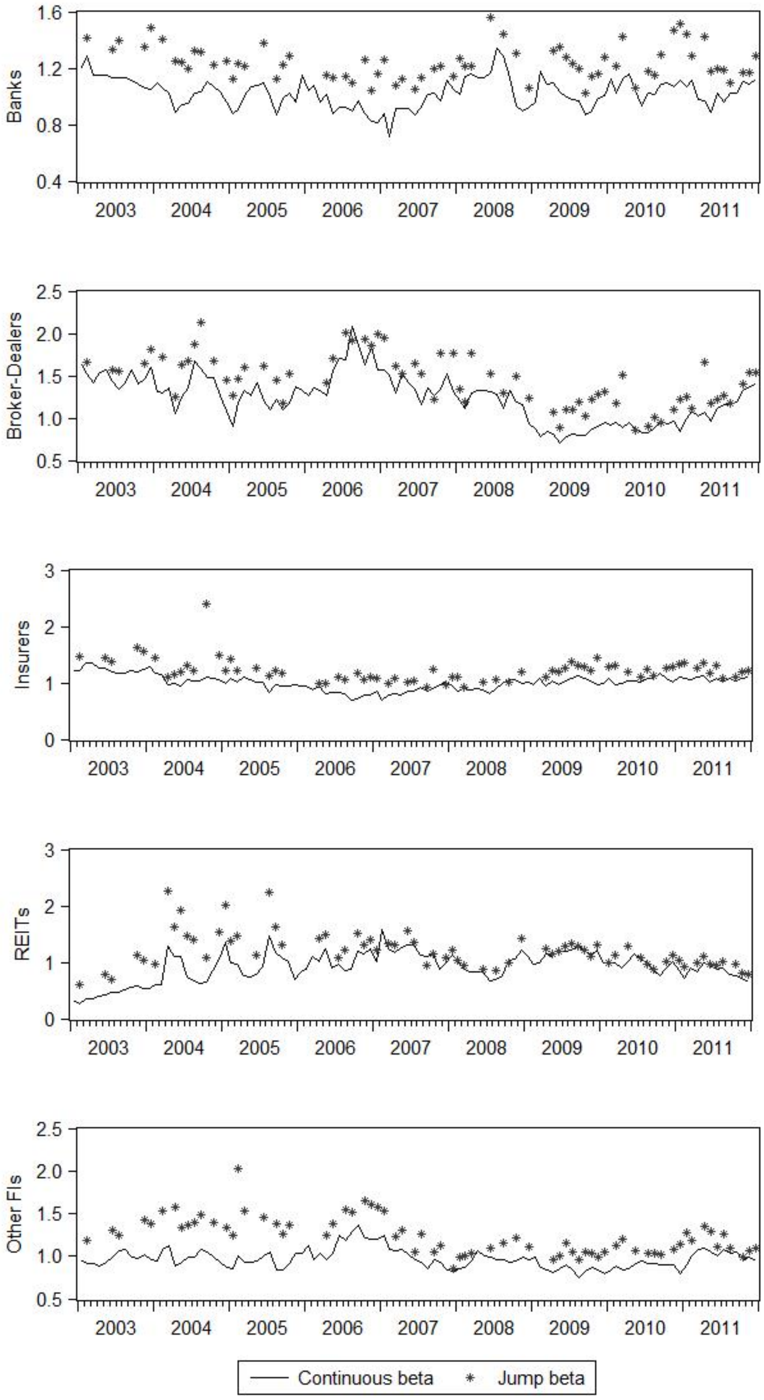
	Total sample period 2003/01-2011/12	Pre-crisis period 2003/01-2007/06	Crisis period 2007/07-2009/05	Post-crisis period 2009/06- 2011/12
	Continuous beta: mean (standard deviation)			
Overall	1.00 (0.32)	1.00 (0.36)	1.00 (0.28)	1.00 (0.30)
Banks	1.03 (0.28)	1.00 (0.30)	1.07 (0.23)	1.03 (0.26)
Dealers	1.24 (0.34)	1.42 (0.28)	1.18 (0.37)	0.99 (0.23)
Insurers	1.00 (0.32)	1.00 (0.27)	0.94 (0.33)	1.05 (0.38)
REITs	0.92 (0.33)	0.87 (0.40)	0.98 (0.22)	0.98 (0.24)
Others	0.97 (0.34)	1.02 (0.41)	0.92 (0.24)	0.92 (0.27)
	Jump beta: mean (standard deviation)			
Overall	1.24 (0.44)	1.32 (0.47)	1.15 (0.40)	1.18 (0.39)
Banks	1.24 (0.31)	1.23 (0.27)	1.26 (0.36)	1.24 (0.33)
Dealers	1.44 (0.44)	1.65 (0.38)	1.41 (0.49)	1.21 (0.34)
Insurers	1.22 (0.49)	1.25 (0.44)	1.07 (0.52)	1.25 (0.52)
REITs	1.21 (0.40)	1.37 (0.47)	1.08 (0.25)	1.06 (0.26)
Others	1.24 (0.34)	1.42 (0.71)	1.07 (0.32)	1.11 (0.33)

Note: The crisis period defined in table is based on the crisis period identified in Chapter 2.

declining since early 2000. We observe relatively smaller jump betas for the crisis period (compared with pre-crisis and post-crisis level), despite the fact that there was a series of events providing information to the market during the crisis period. These results combined with results for market volatilities suggest that increasing market uncertainties (volatilities) do not necessarily lead to increases in the systematic jump risk response of financial firms. In other words, the financial sector was priced as less risky during the period associated with rising leverage and financial sector risk (Caporale, 2012). A possible explanation for this decrease in systematic jump risk of financial firms during the crisis period is the government intervention in the financial markets through TARP, bailouts, capital injection, credit guarantees and liquidity support programs. The financial firms in the sample are relatively large financial firms, so may be judged ‘too big to fail’ and have had government support. Such stocks may not react aggressively to the arrival of new information in the market. This reasoning aligns with lack of significant jumps in any trading days during September 2008 - around the collapse of Lehman Brothers.

Figure 5.3 shows the average cross-sectional continuous and jump betas at sub-

Figure 5.3: Cross-sectional average betas at sub-sectoral level



sectoral level indicating the composition of systematic risk within the financial sector. During the pre-crisis period, broker-dealers exhibit the highest level of response to systematic risk, both continuous and jump, as shown in Table 5.3. During the crisis period, the broker-dealers continue to have the highest level of response to systematic risk amongst financial firms, although this has decreased compared with pre-crisis levels. However, the banks exhibit an increase in both continuous and jump response to systematic risk during the GFC whereas REITs experience only an increase in the continuous response to systematic risk. The level of systematic risk response for the post-crisis period for banks, broker-dealers and insurers is similar. We performed pairwise mean tests across sub-sectors across different sampling window; we find that broker-dealers in respective pairs have significantly higher systematic risk exposure before and during the GFC but not after the GFC at least while pairing it with banks and insurers.

The results also reveal that banks and insurers have similar systematic risk, although during the GFC banks exhibit higher systematic risk than insurers.[5] The similar time-varying structure of continuous and jump betas of banks and insurance companies casts doubt on arguments about different risk structure for these two types of financial institutions, at least while observing their stock price processes. Our results align with Brownlees and Engle (2012) and Dungey et al. (2014) who argue that insurers are as systemically risky as banks. Figure 3 further reveals that REITs tend to have lowest continuous systematic risk response compared with other sub-sectors, although they exhibit very high systematic jump risk parameters during 2004-2005 which aligns with the real estate bubble in REIT stocks.

[5]When we performed pairwise mean test for banks and insurers, the null of no singnificant difference was rejected only for the crisis period.

5.4.3 Systematic and Systemic Risks

In this section we examine the relationship between systematic jump risk responses and the systemic risk of the financial firms. This chapter is the first to establish this relationship empirically. Brownlees and Engle (2012) implement Acharya et al. (2010) and identify the systemic capital shortfall risk for each financial firm. The $SRISK$ index of Brownlees and Engle (2012) ranks the US financial firms (including the majority of firms in our sample) on a weekly basis through the Volatility Institute (VLab) of New York University.[6] The $SIFIRank$ index of Dungey et al. (2012) ranks the systemic risk of financial firms determined by the interconnectedness amongst firms (Dungey et al., 2012). We use these two systemic risk measures for our sample firms and formalize the relationship between systematic risk, in particular, systematic jump risk and the systemic risk in a panel regression model as follows:

$$\beta_{i,t}^{J} = \gamma_1 VLB_{i,t} + \gamma_2 DLV_{i,t} + X_{i,t}\varphi + \delta_i + u_{i,t} \tag{5.17}$$

where VLB is the $SRISK$ ranking of V-Lab, DLV is the $SIFIRank$ index of Dungey et al. (2012), X is a row vector of control variables, γs and φ (a column vector) are parameters of interest, δ is an intercept and u are residuals. Subscripts i and t refer to firm and time respectively. The corporate finance literature suggests that firm characteristics also affect the systematic risk of the firm (Campbell et al., 2010; Hamada, 1972; Mandelker and Rhee, 1984; Subrahmanyam and Thomadakis, 1980). Therefore, we use three control variables: firm size (SIZ - log of equity market capitalization), liquidity (LIQ - liquid assets to total assets), and leverage (LEV - total debt to total assets) to capture firm characteristics. We include one additional control variable, implied market volatility (ΔVIX, log difference of VIX index close) to capture the impact of market volatility. The data for VIX are downloaded from Chicago Board Options Exchange (CBOE)

[6] Available in `http://vlab.stern.nyu.edu/welcome/risk`

website[7] and data for other explanatory variables are available from Thomson Reuters Datastream and compiled in Dungey et al. (2012).[8]

Table 5.4: Correlation matrix

	β^J	DLV	VLB	ΔVIX	LIQ	SIZ	LEV
β^J	1.00						
DLV	0.15	1.00					
VLB	-0.39	-0.03	1.00				
ΔVIX	0.00	-0.02	0.07	1.00			
LIQ	-0.10	0.25	0.28	-0.01	1.00		
SIZ	-0.15	-0.65	0.10	0.05	-0.24	1.00	
LEV	0.20	-0.18	-0.60	-0.03	-0.60	0.17	1.00

We restrict our sample to match data available for systemic risk measures (VLB and DLV). Doing this limits our sample size to 56 firms and sample period to January 2005 to December 2011 which includes 56 months that have at least one jump.

Table 5.4 provides the correlation matrix of our variables of interest in Eq.(5.17). The table suggests that systemic risk measures are highly correlated with some firm characteristic variables. For example, the $SIFIRank$ index (DLV) is highly correlated with the size of the firm and the $SRISK$ index (VLB) is highly correlated with the leverage ratio, consistent with underlying tenets of these systemic risk indices (see Acharya et al., 2010; Brownlees and Engle, 2012; Dungey et al., 2012).[9] The table also reveals a relatively high correlation between leverage and liquidity. The literature on corporate finance suggests there the firm characteristic variables are interrelated (Ozkan, 2001; Rajan and Zingales, 1995). Hence, considering the possible multicollinearity issue amongst the explanatory variables, we estimate Eq.(5.17) with alternative combinations of explanatory variables.

The results reported in Table 5.5 reveal that both the systemic risk measures have significant influence on systematic jump risk; VLB and DLV have statis-

[7] `http://www.cboe.com/micro/vix/historical.aspx`, accessed on 03/12/2012.

[8] Data for liquidity (LIQ) is available only on quarterly frequency. So we use available quarterly data for respective months in the given quarter.

[9] In $SIFIRank$ index of Dungey et al. (2012), each firm is assigned with its relative weight in the network based on relative firm characteristics and in $SRISK$ index of Acharya et al. (2010) and Brownlees and Engle (2012), equity capital is the fundamental input.

Table 5.5: Panel fixed effects regression results

Model	Dependent variable: Jump beta (β^J)					
specifications	(1)	(2)	(3)	(4)	(5)	(6)
VLB	-0.0013***	-0.0013***			-0.0009***	-0.0009***
	(0.0003)	(0.0003)			(0.0003)	(0.0003)
DLV	0.0033***	0.0034***	0.0039***	0.0048***		0.0025***
	(0.0008)	(0.0008)	(0.0009)	(0.0010)		(0.0008)
ΔVIX		0.0339	0.0108	-0.0053	0.0538*	0.0486
		(0.0301)	(0.0270)	(0.0281)	(0.0305)	(0.0298)
LIQ		-0.1322		-0.0329		-0.1344
		(0.1329)		(0.1194)		(0.1275)
LEV			0.0029***			0.0007
			(0.0009)			(0.0008)
SIZ					-0.1189***	-0.0821
					(0.0394)	(0.0502)
$Constant$	1.2154***	1.2175***	1.0208***	1.0198***	4.0675***	3.1054**
	(0.0478)	(0.0481)	(0.0320)	(0.0348)	(0.8988)	(1.1672)
R-sq: overall	0.1597	0.1648	0.0662	0.0242	0.0947	0.1188
N	3076	3076	3076	3076	3076	3076

Note: The variables VLB is the $SRISK$ ranking index of V-Lab, DLV is the $SIFIRank$ ranking index of Dungey et al. (2012), ΔVIX is the log difference of VIX closing index, LIQ is the ratio of liquid assets to total assets, LEV is the ratio of total debt to total assets, and SIZ is the log of equity market capitalization. The sample period used for the estimation is Janaury 2005 to December 2011 using daily data. Huber/White/sandwich standard errors are in parenthesis. ***, **, and * indicate statistical significance at 1%, 5% and 10% levels, respectively.

tically significant coefficients across all the model specifications. In the case of VLB, the coefficients are negative, which implies that financial firms with higher capital risk tend to have higher systematic jump risk. Note that smaller values of the VLB index suggest higher capital shortfall risk. The literature on bank capital and risk taking also suggests that banks engaging in riskier projects tend to have lower capital (Altunbas et al., 2007; Boyd and De Nicolo, 2005; Kwan and Eisenbeis, 1997), therefore, such firms are more responsive to market shocks. The estimated relationships between DLV and the systematic jump risk have positive coefficients. As smaller values of the DLV index indicate higher level of interconnectedness in the network, the results suggest an inverse relationship between interconnectedness and systematic jump risk, indicating that interconnected financial firms are less responsive to market jumps. In other words, financial firms with stronger network connections tend to share risk through networks and therefore are more resilient to jumps in the market.

The marginal effects of both systemic risk indices are small. For example, a 1 unit change in the DLV $SIFIRank$ index changes jump beta by only 0.0033 unit and a 1 unit change in VLB $SRISK$ index changes jump beta by 0.0013. To change jump beta to 1.25 from its mean level of 1.24 would require an increase of 3 in the $SIFIRank$ index or a decrease of 8 in the VLB $SRISK$ index. Therefore, firms interconnectedness and/or expected capital shortfall risk has to change dramatically to affect the jump beta. Brownlees and Engle (2012) and Dungey et al. (2012) show that the respective systemic risk indices can move quite a long way rapidly, particularly during stressful periods, in which case we may also see the changes in jump beta.

The results for control variables indicate that although the implied market volatility has some positive effect on systematic jump risk, the relationship is weak - the coefficient for ΔVIX is significant only in Model 5 suggesting that changes in market volatility (risk) are less likely to explain systematic risk, particularly for the financial firms. This result is consistent with our findings in Section 5.4.1

and 5.4.2 where we observed fewer jumps and relatively small jump betas during the periods of high market volatility. Another possible explanation is that as VIX measures the implied volatilities of S&P 500 index options, and as evident from Figure 1, where the financial sector has a different pattern of volatilities, VIX may not be a close proxy of market volatilities for financial firms.

Firm characteristics such as leverage and firm size have significant explanatory power in explaining systematic jump risk. The results reveal that financial firms with higher leverage (debt capital) are more responsive to jumps in the market. As higher leverage ratios make financial firms riskier, these highly leveraged firms are more sensitive to market jumps. This finding supports our earlier findings for VLB. The estimated results for firm size suggest that smaller firms tend to have larger jump betas than larger firms. Jiang and Yao (2013) also report that small stocks have higher jump returns. Our results for firm liquidity, however, suggest an insignificant inverse relationship with liquidity. The literature suggests that a higher level of liquidity provides financial firms with the flexibility to cope with market shocks (price discontinuities).

Our sample period includes the global financial crisis, and therefore we check for a potential structural shift and break during the GFC in Eq.(5.17) using a dummy variable and dummy interactive variables for each model specification in Table 5.5. We do not find any evidence for structural shift in any of the model specifications - the coefficient for the crisis dummy is not significant. However, we do find some evidence of structural breaks. For example, during the crisis period VIX exhibits a positive and significant coefficient in all model specifications and liquidity tends to have a statistically significant negative coefficient.

5.5 Concluding Remarks

This chapter identifies jumps in the US financial sector and estimates the systematic risk responses to these jumps for the panel of 73 large US financial firms for the period of 2003-2011 using high frequency data. It then examines the relationship between systematic jump risk (jump beta) and the capital shortfall systemic risk measures of Acharya et al. (2010) and the interconnectedness systemic risk measure of Dungey et al. (2012).

Of 108 months in the sample, we find at least one significant jump in the financial sector index for 70 months and that financial firms respond aggressively to jumps in the market. The jump betas are consistently greater than 1 and larger than continuous betas suggesting the importance of including jumps in modeling the price process and the relevance of jump beta in portfolio management. Amongst the financial institutions, banks tend to have lower systematic risk exposure than broker-dealers but higher than insurers. The results for a relationship between systematic jump risk and systemic risk reveal that financial institutions with higher capital shortfall risk also have higher jump risk response, whereas more interconnected financial institutions tend to have lower jump risk response. Firm characteristics such as leverage and size also have significant effect on systematic jump risk and equity capital reduces systematic jump risk. Therefore, higher equity capital for financial firms works as a cushion against risk.

Chapter 6

Conclusion

This dissertation examines the contagion effects of the financial crisis that began in the US in 2007 and spread to become a global financial crisis affecting a large number of other economies. The definition of contagion in the existing literature is contested. This dissertation concentrates on comparing the empirical evidence for contagion using several alternative specifications to test for its existence and relative contribution to observed market volatility. The first model considers contagion measured as the effect of an idiosyncratic shock originating from the US. A latent factor model approach provides evidence of contagion effects via idiosyncratic shocks across the world's largest advanced and emerging economies.

Applications of contagion tests in the existing literature largely consider equity market evidence, and in cross-country studies this is usually represented with market index data. We compare results using this measure with those for financial sector index data for each country. This explicitly addresses the issue of whether the financial sector is primarily responsible for transmitting crises internationally via contagion. Surprisingly, the results from Chapters 2 and 3 indicate less evidence of contagion in the financial sector indices than in the overall market indices. We check the robustness of these results by implementing a conditional factor model, complementing to the initial unconditional model, and find the results are qualitatively similar.

The second modeling approach applied in this dissertation divides contagion into four potential channels: (i) transmissions through common shocks, which impact all the markets simultaneously, although with potentially different factor loadings, (ii) transmissions through idiosyncratic shocks from the crisis originating market, akin to the latent factor model (iii) potential structural shifts in the relationship between markets, analogous to the concept of shift contagion in Forbes and Rigobon (2002), and finally (iv) transmissions via volatility shocks. The evidence from 49 international banking markets supports the existence of contagion effects, although the dominant contagion channels differs across economies, as analysed in Chapter 4.

These alternative, but complementary, approaches all lead to the conclusion that contagion effects are evident across equity markets worldwide, in both the banking sector and overall market indices. The specific results for each chapter build understanding of the international propagation of crises via the avenue of contagion.

In Chapter 2, we examine contagion from the US to the equity markets of the world's largest advanced and emerging economies. The focus in this chapter is to test for idiosyncratic contagion and its contribution to market volatility. The results reveal that the equity markets show evidence of contagion and this effect can explain a large proportion of market volatility. For some emerging economies, such as India and Russia, the contribution of contagion to market volatility exceeds that detected in the advanced economies. However, when we assess contagion effects across the financial sectors of these economies, contagion explains a very small proportion of sectoral level volatility in the advanced economies.

In Chapter 3, we assess contagion through a common factor channel, and find evidence for its existence in the equity markets of both advanced and emerging economies. We find a significant break in the structural relationship between markets at both the aggregate equity index level as well as at financial sector level. The clear evidence of structural breaks across a wide variety of markets strongly supports the need to accommodate this feature in modeling contagion.

In Chapter 4, we propose a model to examine contagion from the four possible contagion channels outlined above, and use it to assess evidence for contagion in banking sectors around the world. We find significant contagion in most of the banking sectors considered. The form of contagion varies across the sample, although when contagion is present, shift contagion is always evident. When we examine which form of contagion lead to systemic banking crises, we find that idiosyncratic contagion increases the probability of systemic crisis by 27 percent. Consequently, policy makers need to pay due attention to idiosyncratic shock channel in responding contagion and attempting to mitigate the crises effects.

The potential risk of contagion, and the consequent systemic risk in the banking sector, prompts an investigation of how financial firms respond to market shocks in Chapter 5. We consider the evidence for responses to discontinuous movements in the high frequency equity prices for US financial institutions using a recent approach to distinguish beta in response to continuous market movements from beta associated with jumps. Jumps often represent the significant effects of new information arrival to the market. We find that financial firms respond to jumps aggressively, and this is particularly the case for firms with higher capital shortfall systemic risk.

In summary, the dissertation corroborates the existence of financial contagion and its contribution to market volatility during the 2007-2009 crisis period across a variety of empirical approaches. However, an important issue which arises from our research is to identify what kinds of policy interventions might be effective in mitigating the contagion effects. These interventions would target policy responses tailored to shutting down the effects of transmission uniquely associated with the crisis origin, rather than focus on the systematic and volatility effects which seem to be relatively well addressed in the current environment. Some examples which may fit in this category include short-sales restrictions, and capital flow restrictions, both of which are widely regarded as having had some success in containing the geographic spread of crises in the past. Other innovative approaches are needed to provide the regulatory authorities with a wide-ranging armament with which to meet the challenges of future crisis events.

Policy makers around the world, at national and supranational levels, are currently developing macro-prudential regulations which aim to prevent, manage and mitigate future financial crises and associated contagion effects. The key concerns are ensuring that the global financial system is resilient to crisis shocks, reducing systemic risk, and managing crises when they do occur. A new strand of academic and policy research has emerged to address these issues in the aftermath of the recent crisis (e.g. Acharya et al. 2010; Adrian and Brunnermeier 2011; Allen and Babus 2009; Dungey et al. 2012; Hanson et al. 2011). The results from Chapter 4 and 5 of this dissertation point to the importance of capital regulation (via leverage) in addressing systemic and systematic risk, and support a future research agenda which explores the possible means of detecting and managing global SIFIs. The contagion results support the importance of SIFIS in the international financial system, and prompt further consideration of the role international and domestic regulatory policy around these financial institutions may play in preventing and mitigating the international transmission of such crises.

Bibliography

Acharya, V. V., I. Drechsler, and P. Schnabl (2014). A pyrrhic victory? Bank bailouts and sovereign credit risk. *Journal of Finance 69*(6), 2689–2739.

Acharya, V. V., R. Engle, and M. Richardson (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review 102*(3), 59–64.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. P. Richardson (2010). Measuring systemic risk. Working Paper 02, Federal Reserve Bank of Cleveland.

Acharya, V. V. and P. Schnabl (2010). Do global banks spread global imbalances? Asset-backed commercial paper during the financial crisis of 2007–09. *IMF Economic Review 58*(1), 37–73.

Adler, G. (2012). Intertwined sovereign and bank solvencies in a model of self-fulfilling crisis. Working Paper 178, International Monetary Fund.

Adrian, T. and M. K. Brunnermeier (2011). CoVaR. Working Paper 17454, National Bureau of Economic Research.

Aggarwal, R., C. Inclan, and R. Leal (1999). Volatility in emerging stock markets. *Journal of Financial and Quantitative Analysis 34*(1), 33–55.

Ait-Sahalia, Y., J. Andritzky, A. Jobst, S. Nowak, and N. Tamirisa (2012). Market response to policy initiatives during the global financial crisis. *Journal of International Economics 87*(1), 162–177.

Ait-Sahalia, Y. and J. Jacod (2012). Analyzing the spectrum of asset returns: Jump and volatility components in high frequency data. *Journal of Economic Literature 50*, 1007–1050.

Alexeev, V., M. Dungey, and W. Yao (2014). Continuous and jump betas with application for portfolio management. Working Paper, University of Tasmania.

Allen, F. and A. Babus (2009). Networks in finance. Working Paper 08-07, Wharton Financial Institutions Center.

Allen, F. and D. Gale (2000). Financial contagion. *Journal of Political Economy 108*(1), 1–33.

Allen, F., A. Hryckiewicz, O. Kowalewski, and G. Tumer-Alkan (2014). Transmission of financial shocks in loan and deposit markets: Role of interbank borrowing and market monitoring. *Journal of Financial Stability 15*, 112–126.

Allen, L., T. G. Bali, and Y. Tang (2012). Does systemic risk in the financial sector predict future economic downturns? *Review of Financial Studies 25*(10), 3000–3036.

Aloui, R., M. S. B. Aissa, and D. K. Nguyen (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? *Journal of Banking and Finance 35*(1), 130–141.

Altunbas, Y., S. Carbo, E. P. M. Gardener, and P. Molyneux (2007). Examining the relationships between capital, risk and efficiency in European banking. *European Financial Management 13*(1), 49–70.

Andersen, T. G., T. Bollerslev, and F. X. Diebold (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *Review of Economics and Statistics 89*(4), 701–720.

Bae, K. H., A. Karolyi, and R. Stulz (2003). A new approach to measuring financial contagion. *Review of Financial Studies 16*(3), 717–763.

Baig, T. and I. Goldfajn (1999). Financial market contagion in the Asian crisis. *IMF Staff Papers 46*, 167–195.

Baker, M. and J. Wurgler (2013). Do strict capital requirements raise the cost of capital? Banking regulation and the low risk anomaly. Working Paper 19018, National Bureau of Economic Research.

Barndorff-Nielsen, O. E. and N. Shephard (2004). Power and bipower variation with stochastic volatility and jumps. *Journal of Financial Econometrics 2*(1), 1–37.

Barndorff-Nielsen, O. E. and N. Shephard (2006). Econometrics of testing for jumps in financial economics using bipower variation. *Journal of Financial Econometrics 4*(1), 1–30.

Baur, D. G. (2012). Financial contagion and the real economy. *Journal of Banking and Finance 36*(10), 2680–2692.

Beck, T., A. Demirguc-Kunt, and R. Levine (2006). Bank concentration, competition, and crises: First results. *Journal of Banking and Finance 30*(5), 1581–1603.

Bekaert, G., M. Ehrmann, M. Fratzscher, and A. J. Mehl (2014). The global crises and equity market contagion. *Journal of Finance 69*(6), 2597–2649.

Bekaert, G. and C. R. Harvey (1995). Time-varying world market integration. *Journal of Finance 50*(2), 403–444.

Bekaert, G., C. R. Harvey, and A. Ng (2005). Market integration and contagion. *Journal of Business 78*(1), 39–70.

Bekaert, G., R. J. Hodrick, and X. Zhang (2009). International stock return comovements. *Journal of Finance 64*(6), 2591–2626.

Benetrix, A. S. and P. R. Lane (2015). International differences in fiscal policy during the global crisis. *Fiscal Studies 36*(1), 1–27.

Berger, A. N. and C. H. Bouwman (2013). How does capital affect bank performance during financial crises? *Journal of Financial Economics 109*(1), 146–176.

BIS (2009). The international financial crisis: Timeline, impact and policy responses in Asia and the Pacific. Technical Report, Bank for International Settlements.

BIS (2010). The Basel Committee's response to the financial crisis: Report to the G20. Technical Report, Bank for International Settlements.

Bollerslev, T., V. Todorov, and S. Z. Li (2013). Jump tails, extreme dependencies, and the distribution of stock returns. *Journal of Econometrics 172*(2), 307–324.

Bordo, M., B. Eichengreen, D. Klingebiel, and M. S. Martinez-Peria (2001). Is the crisis problem growing more severe? *Economic Policy 16*(32), 51–82.

Boyd, J. and G. De Nicolo (2005). The theory of bank risk taking and competition revisited. *Journal of Finance 60*(3), 1329–1343.

Boyer, B. H., T. Kumagai, and K. Yuan (2006). How do crises spread? Evidence from accessible and inaccessible stock indices. *Journal of Finance 61*(2), 957–1003.

Boyson, N. M., C. W. Stahel, and R. M. Stulz (2010). Hedge fund contagion and liquidity shocks. *Journal of Finance 65*(5), 1789–1816.

Brealey, R. A., I. A. Cooper, and E. Kaplanis (2012). International propagation of the credit crisis: Lessons for bank regulation. *Journal of Applied Corporate Finance 24*(4), 36–45.

Bretschger, L., V. Kappel, and T. Werner (2012). Market concentration and the likelihood of financial crises. *Journal of Banking and Finance 36*(12), 3336–3345.

Brownlees, C. and R. Engle (2012). Volatility, correlation and tails for systemic risk measurement. Working Paper, New York University.

Busetti, F. and A. Harvey (2011). When is a copula constant? A test for changing relationships. *Journal of Financial Econometrics 9*(1), 106–131.

Calvo, G. A. and E. G. Mendoza (2000). Capital-markets crises and economic collapse in emerging markets: An informational-frictions approach. *American Economic Review 90*(2), 59–64.

Campbell, J. Y., C. Polk, and T. Vuolteenaho (2010). Growth or glamour? Fundamentals and systematic risk in stock returns. *Review of Financial Studies 23*(1), 305–344.

Caporale, T. (2012). Time varying CAPM betas and banking sector risk. *Economics Letters 115*(2), 293–295.

Caporin, M., L. Pelizzon, F. Ravazzolo, and R. Rigobon (2013). Measuring sovereign contagion in Europe. Working Paper 18741, National Bureau of Economic Research.

Cavaglia, S., C. Brightman, and M. Aked (2000). The increasing importance of industry factors. *Financial Analysts Journal 56*(5), 41–54.

Cetorelli, N. and L. S. Goldberg (2011). Global banks and international shock transmission: Evidence from the crisis. *IMF Economic Review 59*(1), 41–76.

Chatrath, A., H. Miao, S. Ramchander, and S. Villupuram (2014). Currency jumps, cojumps and the role of macro news. *Journal of International Money and Finance 40*, 42–62.

Chiang, M.-H. and L.-M. Wang (2011). Volatility contagion: A range-based volatility approach. *Journal of Econometrics 165*(2), 175–189.

Chiang, T. C., B. N. Jeon, and H. Li (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance 26*(7), 1206–1228.

Chiang, T. C. and D. Zheng (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking and Finance 34*(8), 1911–1921.

Cihak, M., A. Demirguc-Kunt, E. Feyen, and R. Levine (2012). Benchmarking financial systems around the world. Working Paper 6175, World Bank.

Cole, R. (2012). How did the financial crisis affect small business lending in the United States? Technical Report 399, US Small Business Administration.

Corsetti, G., M. Pericoli, and M. Sbracia (2005). Some contagion, some interdependence: More pitfalls in tests of financial contagion. *Journal of International Money and Finance 24*(8), 1177–1199.

Das, S. R. and R. Uppal (2004). Systemic risk and international portfolio choice. *Journal of Finance 59*(6), 2809–2834.

de Bandt, O. and P. Hartmann (2000). Systemic risk: A survey. Working Paper 35, European Central Bank.

De Jonghe, O. (2010). Back to the basics in banking? A micro-analysis of banking system stability. *Journal of Financial Intermediation 19*(3), 387–417.

Diamond, D. W. and P. H. Dybvig (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy 91*(3), 401–419.

Diebold, F. X. and K. Yilmaz (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal 119*(534), 158–171.

Dornbusch, R., Y. C. Park, and S. Claessens (2000). Contagion: Understanding how it spreads. *World Bank Research Observer 15*(2), 177–197.

Dumitru, A.-M. and G. Urga (2012). Identifying jumps in financial assets: A comparison between nonparametric jump tests. *Journal of Business and Economic Statistics 30*(2), 242–255.

Dungey, M., R. Fry, B. Gonzalez-Hermosillo, and V. Martin (2005). Empirical modelling of contagion: A review of methodologies. *Quantitative Finance 5*(1), 9–24.

Dungey, M., R. Fry, B. Gonzalez-Hermosillo, and V. Martin (2011). *Transmission of Financial Crises and Contagion: A Latent Factor Approach.* Oxford University Press.

Dungey, M., M. Luciani, and D. Veredas (2012). Ranking systemically important financial institutions. CAMA Working Paper 47, Centre for Applied Macroeconomic Analysis, Australian National University.

Dungey, M., M. Luciani, and D. Veredas (2014). The emergence of systemically important insurers. Working Paper 38, Centre for International Finance and Regulation.

Dungey, M. and V. Martin (2001). Contagion across financial markets: An empirical assessment. *New York Stock Exchange Conference Paper*, 16–17.

Dungey, M. and V. Martin (2007). Unravelling financial market linkages during crises. *Journal of Applied Econometrics 22*(1), 89–119.

Dungey, M., M. D. McKenzie, and A. Yalama (2013). The cross market effects of short sale restrictions. *North American Journal of Economics and Finance 26*, 53–71.

Dungey, M. and E. Renault (2013). Identifying contagion. Menuscript, University of Tasmania.

Edwards, S. (1998). Interest rate volatility, capital controls, and contagion. Working Paper 6756, National Bureau of Economic Research.

Edwards, S. and R. Susmel (2001). Volatility dependence and contagion in emerging equity markets. *Journal of Development Economics 66*(2), 505–532.

Eichengreen, B., A. Rose, and C. Wyplosz (1996). Contagious currency crises: First tests. *Scandinavian Journal of Economics 98*(4), 463–484.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica 50*(4), 987–1007.

Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business and Economic Statistics 20*(3), 339–350.

Engle, R. F., T. Ito, and W. L. Lin (1990). Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica 58*(3), 525–542.

Eraker, B. (2004). Do stock prices and volatility jump? Reconciling evidence from spot and option prices. *Journal of Finance 59*(3), 1367–1404.

Eraker, B., M. Johannes, and N. Polson (2003). The impact of jumps in volatility and returns. *Journal of Finance 58*(3), 1269–1300.

Favero, C. A. and F. Giavazzi (2002). Is the international propagation of financial shocks non-linear?: Evidence from the ERM. *Journal of International Economics 57*(1), 231–246.

Fecht, F., H. P. Gruner, and P. Hartmann (2012). Financial integration, specialization, and systemic risk. *Journal of International Economics 88*(1), 150–161.

Ferson, W. E. and C. R. Harvey (1993). The risk and predictability of international equity returns. *Review of Financial Studies 6*(3), 527–566.

Forbes, K. J. and R. Rigobon (2002). No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance 57*(5), 2223–2261.

Fratzscher, M. (2012). Capital flows, push versus pull factors and the global financial crisis. *Journal of International Economics 88*(2), 341–356.

Gagnon, J., M. Raskin, J. Remache, and B. Sack (2011). The financial market effects of the Federal Reserve's large-scale asset purchases. *International Journal of Central Banking 7*(1), 3–43.

Gauthier, C., A. Lehar, and M. Souissi (2012). Macroprudential capital requirements and systemic risk. *Journal of Financial Intermediation 21*(4), 594–618.

Ghysels, E. and A. Hall (1990). A test for structural stability of Euler conditions parameters estimated via the generalized method of moments estimator. *International Economic Review 31*(2), 355–364.

Gilchrist, S., J. W. Sim, and E. Zakrajsek (2013). Misallocation and financial market frictions: Some direct evidence from the dispersion in borrowing costs. *Review of Economic Dynamics 16*(1), 159–176.

Girardin, E. and Z. Liu (2007). The financial integration of China: New evidence on temporally aggregated data for the A-share market. *China Economic Review 18*(3), 354–371.

Glick, R. and A. K. Rose (1999). Contagion and trade: Why are currency crises regional? *Journal of International Money and Finance 18*(4), 603–617.

Goldstein, M. (1998). *The Asian Crisis: Causes, Cures, and Systematic Implications.* Institute for International Economics.

Graham, J. R. and C. R. Harvey (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics 60*, 187–243.

Hall, A. R. (2005). *Generalized Method of Moments.* Oxford University Press.

Hamada, R. S. (1972). The effect of the firm's capital structure on the systematic risk of common stocks. *Journal of Finance 27*(2), 435–452.

Hamao, Y., R. Masulis, and V. Ng (1990). Correlations in price changes and volatility across international stock markets. *Review of Financial Studies 3*(2), 281–307.

Hansen, P. R. and A. Lunde (2005). A forecast comparison of volatility models: Does anything beat a GARCH(1,1)? *Journal of Applied Econometrics 20*(7), 873–889.

Hanson, S. G., A. K. Kashyap, and J. C. Stein (2011). A macroprudential approach to financial regulation. *Journal of Economic Perspectives 25*(1), 3–28.

Hasman, A. (2013). A critical review of contagion risk in banking. *Journal of Economic Surveys 27*(5), 978–995.

Huang, X. and G. Tauchen (2005). The relative contribution of jumps to total price variance. *Journal of Financial Econometrics 3*(4), 456–499.

Hwang, E., H. Min, B. Kim, and K. H. (2013). Determinants of stock market comovements among US and emerging economies during the US financial crisis. *Economic Modelling 35*, 338–348.

IMF (2009a). IMF country report. Technical Report 09/211, International Monetary Fund.

IMF (2009b). IMF country report. Technical Report 09/231, International Monetary Fund.

IMF (2009c). IMF country report. Technical Report 09/262, International Monetary Fund.

IMF (2009d). IMF country report. Technical Report 09/302, International Monetary Fund.

IMF (2009e). IMF country report. Technical Report 09/128, International Monetary Fund.

IMF (2009f). IMF country report. Technical Report 09/162, International Monetary Fund.

Inclan, C. and G. C. Tiao (1994). Use of cumulative sums of squares for retrospective detection of changes of variance. *Journal of the American Statistical Association 89*(427), 913–923.

Iwatsubo, K. and K. Inagaki (2007). Measuring financial market contagion using dually-traded stocks of Asian firms. *Journal of Asian Economics 18*(1), 217–236.

Iyer, R. and J. L. Peydro (2011). Interbank contagion at work: Evidence from a natural experiment. *Review of Financial Studies 24*(4), 1337–1377.

Jacod, J. and V. Todorov (2009). Testing for common arrivals of jumps for discretely observed multidimensional processes. *Annals of Statistics 37*(4), 1792–1838.

Jagannathan, R. and Z. Wang (1996). The conditional capm and the cross-section of expected returns. *Journal of Finance 51*(1), 3–53.

Jarrow, R. A. and E. R. Rosenfeld (1984). Jump risks and the intertemporal capital asset pricing model. *The Journal of Business 57*(3), 337–351.

Jiang, G. J. and T. Yao (2013). Stock price jumps and cross-sectional return predictability. *Journal of Financial and Quantitative Analysis 48*, 1519–1544.

Joyce, M. A. S., N. McLaren, and C. Young (2012). Quantitative easing in the United Kingdom: Evidence from financial markets on QE1 and QE2. *Oxford Review of Economic Policy 28*(4), 671–701.

Kalemli-Ozcan, S., E. Papaioannou, and F. Perri (2013). Global banks and crisis transmission. *Journal of International Economics 89*(2), 495–510.

Kalemli-Ozcan, S., E. Papaioannou, and J. Peydro (2013). Financial regulation, financial globalization, and the synchronization of economic activity. *Journal of Finance 68*(3), 1179–1228.

Kalemli-Ozcan, S., B. Sorensen, and S. Yesiltas (2012). Leverage across firms, banks, and countries. *Journal of International Economics 88*(2), 284–298.

Kamil, H. and K. Rai (2010). The global credit crunch and foreign banks' lending to emerging markets: Why did Latin America fare better? Working Paper 102, International Monetary Fund.

Kaminsky, G., S. Lizondo, and C. M. Reinhart (1998). Leading indicators of currency crises. *IMF Staff Papers 45*(1), 1–48.

Kaminsky, G. and C. Reinhart (1998). Financial crises in Asia and Latin America: Then and now. *American Economic Review 88*(2), 444–448.

Kaminsky, G. and S. Schmukler (1999). What triggers market jitters?:: A chronicle of the asian crisis. *Journal of International Money and Finance 18*(4), 537–560.

Kasch, M. and M. Caporin (2013). Volatility threshold dynamic conditional correlations: An international analysis. *Journal of Financial Econometrics Advance online publication.*

Kashyap, A., J. C. Stein, and S. G. Hanson (2010). An analysis of the impact of šubstantially heightenedčapital requirements on large financial institutions. Working Paper, Harvard University.

Kawai, M. and S. Takagi (2009). Why was Japan hit so hard by the global financial crisis? Working Paper 153, Asian Development Bank Institute.

Kenourgios, D., A. Samitas, and N. Paltalidis (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money 21*(1), 92–106.

Khoon, G. S. and M. L. Mah-Hui (2010). The impact of the global financial crisis: The case of Malaysia. Working Paper 26, Third World Network.

Kim, S. (2001). International transmission of U.S. monetary policy shocks: Evidence from VAR's. *Journal of Monetary Economics 48*(2), 339–372.

King, M. and S. Wadhwani (1990). Transmission of volatility between stock markets. *Review of Financial Studies 3*(1), 5–33.

Klyuev, V., P. De Imus, and K. Srinivasan (2009). Unconventional choices for unconventional times: Credit and quantitative easing in advanced economies. IMF Staff Position Note 27, International Monetary Fund.

Kodres, L. E. and M. Pritsker (2002). A rational expectations model of financial contagion. *Journal of Finance 57*(2), 769–799.

Kwan, S. and R. Eisenbeis (1997). Bank risk, capitalization, and operating efficiency. *Journal of Financial Services Research 12*(2-3), 117–131.

Kyle, A. S. and W. Xiong (2001). Contagion as a wealth effect. *Journal of Finance 56*(4), 1401–1440.

Laeven, L. and F. Valencia (2013). Systemic banking crises database. *IMF Economic Review 61*(2), 225–270.

Laxton, D. and E. Prasad (2000). International spillovers of macroeconomic shocks: A quantitative exploration. Working Paper 101, International Monetary Fund.

Lee, S. S. and P. A. Mykland (2008). Jumps in financial markets: A new nonparametric test and jump dynamics. *Review of Financial Studies 21*(6), 2535–2563.

Lepetit, L., E. Nys, P. Rous, and A. Tarazi (2008). Bank income structure and risk: An empirical analysis of European banks. *Journal of Banking and Finance 32*(8), 1452–1467.

Mandelker, G. N. and S. G. Rhee (1984). The impact of the degrees of operating and financial leverage on systematic risk of common stock. *Journal of Financial and Quantitative Analysis 19*, 45–57.

Masson, P. (1999). Contagion: Macroeconomic models with multiple equilibria. *Journal of International Money and Finance 18*(4), 587–602.

Merton, R. C. (1976). Option pricing when underlying stock returns are discontinuous. *Journal of Financial Economics 3*(1-2), 125–144.

Miles, D., J. Yang, and G. Marcheggiano (2013). Optimal bank capital. *Economic Journal 123*(567), 1–37.

Miles, J. A. and J. R. Ezzell (1980). The weighted average cost of capital, perfect capital markets, and project life: A clarification. *Journal of Financial and Quantitative Analysis 15*(3), 719–730.

Mirzaei, A., T. Moore, and G. Liu (2013). Does market structure matter on bank's profitability and stability? Emerging vs. advanced economies. *Journal of Banking and Finance 37*(8), 2920–2937.

Mishkin, F. S. (2011). Over the cliff: From the subprime to the global financial crisis. *Journal of Economic Perspectives 25*(1), 49–70.

Mondria, J. and C. Quintana-Domeque (2012). Financial contagion and attention allocation. *Economic Journal*, 1–26.

Moser, T. (2003). What is international financial contagion? *International Finance 6*(2), 157–178.

NBER (2010). Business cycle dating committee report. Technical Report, National Bureau of Economic Research.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica 59*(2), pp. 347–370.

Nicolo, G. D. and M. L. Kwast (2002). Systemic risk and financial consolidation: Are they related? *Journal of Banking and Finance 26*(5), 861–880.

Ocampo, J. A. (2009). Latin America and the global financial crisis. *Cambridge Journal of Economics 33*(4), 703–724.

Ozkan, A. (2001). Determinants of capital structure and adjustment to long run target: Evidence from UK company panel data. *Journal of Business Finance and Accounting 28*(1-2), 175–198.

Pan, J. (2002). The jump-risk premia implicit in options: Evidence from an integrated time-series study. *Journal of Financial Economics 63*(1), 3–50.

Park, Y. C. and C. Y. Song (2001). Institutional investors, trade linkage, macroeconomic similarities, and contagion of the Thai crisis. *Journal of the Japanese and International Economies 15*(2), 199–224.

Pasquariello, P. (2007). Imperfect competition, information heterogeneity, and financial contagion. *Review of Financial Studies 20*(2), 391–426.

Patton, A. J. and M. Verardo (2012). Does beta move with news? Firm-specific information flows and learning about profitability. *Review of Financial Studies 25*(9), 2789–2839.

Polson, N. G. and J. G. Scott (2011). Explosive volatility: A model of financial contagion. Working Paper, University of Chicago.

Popov, A. and G. F. Udell (2012). Cross-border banking, credit access, and the financial crisis. *Journal of International Economics 87*(1), 147–161.

Rajan, R. G. and L. Zingales (1995). What do we know about capital structure? Some evidence from international data. *Journal of Finance 50*(5), 1421–1460.

Reinhart, C. M. and K. S. Rogoff (2009). *This Time is Different: A Panoramic View of Eight Centuries of Financial Crises*. New Jersey: Princeton.

Rose, A. K. and M. M. Spiegel (2010). Cross-country causes and consequences of the 2008 crisis: International linkages and american exposure. *Pacific Economic Review 15*(3), 340–363.

Samarakoon, L. P. (2011). Stock market interdependence, contagion, and the U.S. financial crisis: The case of emerging and frontier markets. *Journal of International Financial Markets, Institutions and Money 21*(5), 724–742.

Sanso, A., V. Arago, and J. L. Carrion (2004). Testing for changes in the unconditional variance of financial time series. *Revista de Economia Financiera 4*, 32–53.

Sbracia, M. and A. Zaghini (2003). The role of the banking system in the international transmission of shocks. *World Economy 26*(5), 727–754.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance 19*(3), 425–442.

Shleifer, A. and R. Vishny (2011). Fire sales in finance and macroeconomics. *Journal of Economic Perspectives 25*(1), 29–48.

Subrahmanyam, M. G. and S. B. Thomadakis (1980). Systematic risk and the theory of the firm. *The Quarterly Journal of Economics 94*(3), 437–451.

Tauchen, G. and H. Zhou (2011). Realized jumps on financial markets and predicting credit spreads. *Journal of Econometrics 160*(1), 102–118.

Todorov, V. and T. Bollerslev (2010). Jumps and betas: A new framework for disentangling and estimating systematic risks. *Journal of Econometrics 157*(2), 220–235.

Upper, C. (2011). Simulation methods to assess the danger of contagion in interbank markets. *Journal of Financial Stability 7*(3), 111–125.

van Rijckeghem, C. and B. Weder (2001). Sources of contagion: Is it finance or trade? *Journal of International Economics 54*(2), 293–308.

van Rijckeghem, C. and B. Weder (2003). Spillovers through banking centers: A panel data analysis of bank flows. *Journal of International Money and Finance 22*(4), 483–509.

Wang, K. M. and T. B. Nguyen Thi (2012). Did China avoid the Asian flu? The contagion effect test with dynamic correlation coefficients. *Quantitative Finance 23*(3), 471–481.

Wang, Y. and A. Di Iorio (2007). Are the China-related stock markets segmented with both world and regional stock markets? *Journal of International Financial Markets, Institutions and Money 17*(3), 277–290.

Wei, L. T. (2009). Combating the global economic crisis: Japan's policies and politics. Working Paper 436, East Asian Institute, National University of Singapore.

Yan, S. (2011). Jump risk, stock returns, and slope of implied volatility smile. *Journal of Financial Economics 99*(1), 216–233.

Yuan, K. (2005). Asymmetric price movements and borrowing constraints: A rational expectations equilibrium model of crises, contagion, and confusion. *Journal of Finance 60*(1), 379–411.

Zhang, B., X. Li, and H. Yu (2013). Has recent financial crisis changed permanently the correlations between BRICS and developed stock markets? *North American Journal of Economics and Finance 26*, 725–738.